Quantifying energy transition pathways: an integrated framework approach

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Quantifying Energy Transition Pathways: An Integrated Framework Approach

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Contents

Abbreviations

ABM	Agent-Based Modelling
A+, A–G	Different residential energy efficiency labels, where G is the least efficient and A+ the most efficient
ABARE	Australian Bureau of Agricultural and Resource Economics
ADEME	French Environment and Energy Management Agency
AIMMS	Advanced Integrated Multidimensional Modeling Software
BU	Bottom-up models
CAES	Compressed Air Energy Storage
CCS	Carbon Capture and Storage
CCU, CCS	Carbon Capture and Utilization
CCUS	Carbon Capture, Utilization, and Storage
CGE	Computable General Equilibrium
CHP	Combined Heat and Power
CNG	Compressed natural gas
CO_2	Carbon dioxide
CTL	Clustered Technological Learning
DAC	Direct Air Capture
DEA	Danish Energy Agency
DES	Discrete Event Simulation
DG ENER	Directorate-General for Energy (European Commission)
DLR	Deutsches Zentrum für Luft- und Raumfahrt (German Aerospace Center)
DP	Dynamic Programming
DSM	Demand Side Management
DTU	Danmarks Tekniske Universitet (Technical University of Denmark)
ECMWF	European Centre for Medium-range Weather Forecasts
ECN	Energy research Centre of the Netherlands (ECN part of TNO)
EIA	U.S. Energy Information Administration
EMOS	Energy Market Observation System
ENSYSI	Energy System Simulation
ENTSO-E	European Network of Transmission System Operators for Electricity
ENTSO-G	European Network of Transmission System Operators for Gas
ESM	Energy System Model
ESOMs	Energy System Optimization Models
ETI	Energy Technology Institute
ETL	Endogenous Technological Learning
ETS	Emission Trading System
ETSAP	Energy Technology Systems Analysis Program
EU	European Union
EV	Electric Vehicle

GAMS	General Algebraic Modeling System
GEA	Global Energy Assessment
GHG	Greenhouse Gas
GIS	Geographic Information System
GTS	Gasunie Transport Service
HD pipeline	High-density pipeline
HDV	Heavy-duty vehicle
HT heat	High-temperature heat
HTR	Hourly Temporal Resolution
HV grid	High Voltage grid
ICE	Internal Combustion Engine
IEA	International Energy Agency
IEM	Integrated energy models
IESA	Integrated Energy System Analysis
IESA-Opt	Integrated Energy System Analysis - Optimization
IIASA	International Institute for Applied Systems Analysis, Austria
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
ISEP	Institute for Sustainable Energy Policies (Japan)
ISUSI	Institute for Sustainable Solutions and Innovations
LD pipeline	Low-density pipeline
LDV	Light-duty vehicle
LP	Linear Programming
LT heat	Low-temperature heat
LULUCF	Land Use, Land-use Change, and Forestry
LV grid	Low Voltage grid
MACC	Marginal Abatement Cost Curve
MAF	Mid-term Adequacy Forecast
MAP	Multi-Agent Programming
MCA	Multi-Criteria Analysis
MCL	Multi-Cluster Learning
MD pipeline	Medium Density pipeline
MILP	Mix-integer linear programming
MIP	Mixed-Integer Programming
MONIT	Monitoring Ontwikkeling Nationaal verbruik, Informatie en Trendanalyse (Netherlands)
MRL	Multi-Regional Learning
MV grid	Medium Voltage grid
NECP	National Energy and Climate Plan
NEO	National Energy Outlook (Netherlands)
OBP	Oil-based Products
OESM	Optimization energy system model
OFCE	French Economic Observatory
OPF	Optimal Power Flow
P2Chemicals	Power to Chemicals
P2G	Power to Gas

P2Gas	Power to Gas
P2H	Power to Hydrogen
P2Heat	Power to Heat
P2Hydrogen	Power to Hydrogen
P2Liquids	Power to Liquids
P2Mobility	Power to Mobility
PBL	The Netherlands Environmental Assessment Agency
PHES	Pumped Hydro Energy Storage
P-to-L, P2L	Power to liquids
P-to-X	Conversion of electricity (power) to a different energy carrier or product (e.g., hydrogen or ammonia)
PV cell	Photo Voltaic cell
SD	System Dynamics
SHT heat	Super-high-temperature heat
SSAS	Solid State Ammonia Synthesis
SSP	Shared Socioeconomic Pathway
TD	Top-down models
TES	Thermal Energy Storage
TNO	Netherlands Organization for Applied Scientific Research
TYNDP	Ten-year Network Development Plan
UNFCCC	United Nations Framework Convention on Climate Change
UoC	Units of Capacity
V2Grid	Vehicle to Grid
VOLL	Value of Lost Load
VRE	Variable Renewable Energy
VRES	Variable Renewable Energy Sources
V-to-G, V2G	Vehicle to grid
WBGU	German Advisory Council on Global Change
wCCS	With carbon capture and storage
WEC	World Energy Council

Nomenclature of the model

Indices

p	Index of the set conformed by all the modelled periods
h	Index of the set conformed by all the hours in a year
d	Index of the set conformed by all the days in a year
a	Index of the activities set
ae	Index of the electricity-related activities subset, A^e
ah	Index of the national heat-related activities subset, A^h
ag	Index of the gas-related activities subset, A^g
t, t_i, t_j	Indices of the technologies set
te	Index of the technologies representing air released emissions in the considered target scope.
td	Index of the dispatchable technologies subset
tp	Index of the operation technologies subset
tf	Index of the flexible technologies subset
tf_b	Index of the flexible technologies of the battery type subset
tc	Index of the flexible CHP technologies subset
ts	Index of the shedding technologies subset
ti	Index of the infrastructure technologies subset

Parameters

$VC_{t,p}$	The variable cost of technology in a period
α_t	Annuity factor of a technology (or, in this case, the inverse)
$IC_{t,p}$	Investment cost of technology in a period
DF_t	Fraction of the capital cost of a technology that remains after premature decommissioning
$RC_{\mathrm{t}_i,t_j,p}$	Retrofitting costs from one technology to another
$FC_{t,p}$	The fixed operational cost of technology in a period
$AB_{t,a,p}$	Activity balance of inputs and outputs of a technology
$V_{a,p}$	Exogenous required activity volumes in a period
Γ_t	Available use of a technology per unit of capacity
E_p	Absolute CO_2 emission target in a certain period.
RM_{t_i,t_j}	Binary matrix specifying which technologies can be retrofitted into others
${S^{min}}_{t,p}, {S^{max}}_{t,p}$	Minimum and maximum allowed installed capacities of technology in a year
$P_{h,tp}$	Hourly availability or reference operational profile of a technology
$AE_{t,a}$	Binary parameter indicating the hourly electricity activities of a technology
$R^{dw}_{td,p}, R^{up}_{td,p}$	Ramping up and down limits of hourly dispatchable technologies
η_{tc}	Only heat reference efficiency of a flexible CHP
ε_{tc}	Only power reference efficiency of a flexible CHP
SC_{ts}	Power shedding of a technology per unit of capacity
$UtP_{ts,p}$	Use-to-power ratio of a shedding technology in a period
SF_{ts}	Maximum allowed shedding fraction of a shedding technology
$AG_{tf,a}$	Binary parameter indicating the gas activities of a technology

FC_{tf}	Flexibility capacity in terms of the impact on the corresponding network of technology.
NN_{tf}	Non-negotiable load of flexible technologies.
CC_{tf}	Charging (or discharging) capacity of a storage technology.
CT_{tf}	Charging time of a storage technology.
VU_{tf}	Hourly profile of the usage of a flexible vehicle (not connected to the grid).
AS_{tf}	Average speed of a flexible vehicle.

Variables

$Symbol$	Description
$u_{t,p}$	Use of technology in a period
$i_{t,p}$	Investments in technology in a period
$d^{pre}{}_{t,p}$	Premature decommissioning of a technology in a period
$r_{t^i,t^j,p}$	Retrofitting from one technology to another in a period
$s_{t,p}$	Stock (installed capacity) of a technology in a period
$d^{cum}{}_{t,p}$	Cumulative decommissioning of a technology in a period
$d^{lt}{}_{t,p}$	Decommissioning of a technology in a period due to lifetime expiry
$u_{h,td,p}$	Hourly use of a dispatchable technology in a period
$\Delta q^{up}{}_{h,tf,p}$	Increase in electricity demand from a flexible technology in an hour in a period
$\Delta q^{dw}{}_{h,tf,p}$	Decrease in electricity demand from a flexible technology in an hour in a period
$\Delta u_{h,tc,p}$	Deviation in use of a flexible CHP technology in an hour in a period
$\Delta p_{h,tc,p}$	Deviation in power output of a CHP technology in an hour in a period
$\Delta u_{h,ts,p}$	Decrease in use of a shedding technology in an hour in a period
$l_{h,tf,p}$	Losses from deviations in use of flexible technologies in an hour in a period
$\Delta q^{max}{}_{h,tf,p}$	Maximum increase limit of power demand of a flexible technology in an hour
$\Delta q^{min}{}_{h,tf,p}$	Maximum decrease limit of power demand of a flexible technology in an hour
$v^{max}{}_{h,tf,p}$	Upper saturation limit from shifted volume in an hour in a period
$v^{min}{}_{h,tf,p}$	Lower saturation limit from shifted volume in an hour in a period
$u_{d,td,p}$	Daily use of a dispatchable technology in a period
$\Delta q^{up}{}_{d,tg,p}$	Upwards deviation in the use of a daily storage technology in a period
$\Delta q^{dw}{}_{d,tg,p}$	Downwards deviation in the use of a daily storage technology in a period

Introduction

1.1. Background

The European Union has set the ambitious goal of achieving net-zero greenhouse gas emissions by 2050. Reaching this goal requires several actions intended to make a transition from a conventional energy system to a low-carbon emitting energy system.

This includes greatly increased use of low-carbon energy sources (such as wind, solar, geothermal, and nuclear power) and new energy carriers (e.g., hydrogen, ammonia, and synthetic fuels). To make the best use of these energy sources we must implement sector coupling (e.g., Power to Heat (P2Heat), Power to Mobility (P2Mobility), Power to Liquids (P2Liquids), and Power to Gas (P2Gas)), storage solutions (e.g., batteries, seasonal thermal energy storage (TES), and compressed air energy storage (CAES)), and demand-side management (e.g., demand response and demand shedding). Furthermore, smarter infrastructure management (such as collective heat networks, smart power distribution, and hydrogen pipelines), and increased social involvement (through prosumers and decentralized generation) must be put in place. Moreover, it is crucial that the entire carbon balance is considered, including energy and non-energy related emissions (such as enteric fermentation, fertilizers, and manure management) and carbon removal schemes, such as, afforestation, bioenergy carbon capture and storage (BECCS), and direct air capture (DAC). In addition, this transition can have a major impact on the whole economy as capital and labor flows are redirected toward the elements mentioned.

Moreover, it is expected that variable renewable energy sources (VRES) such as wind and sun will have a considerable share in electricity generation. Integrating this intermittent generation will require increasing levels of flexibility in both demand and supply from other sources, a flexibility that will not only be provided within the electricity system, but which can also be found in other parts of the energy system that are coupled with the power system, such as in gas supply and demand and in the provision of heat for both space heating and for agriculture and industrial processes.

Understanding the possible interlinkages and interactions between the different parts of this increasingly integrated energy system, such as, P2Mobility and Vehicle to Grid (V2G), will be vital to be able to make the right investment decisions on, among others, infrastructure, energy production and spatial planning, to design policies and regulation which will provide the right incentives and to allow flexibility to be used from within the whole energy system. This will also require insights into the transition path, in the possible ways the energy system can evolve toward a future low-carbon emitting system.

The transition is not only relevant at the national or international level. The energy system at the regional or local level will also go through a transformation when we move towards a low-carbon emitting energy system. Indeed, combining developments at all levels and over various economic, social, and technical domains will be a central issue of the transition. For instance, the requirements for decarbonization of international aviation and navigation can greatly affect the national policies on electricity and fuel prices, carbon price, and required carbon removal.

The combination of different levels in various areas makes the energy transition a complex challenge. Therefore, there is a need for advanced computer models to understand the complex interactions between different energy sources, technologies, and economic and environmental impacts, and to be used to better inform decision-making processes. As a result, Energy System Models (ESMs) have been developed to guide decision-makers in making long-term robust policy decisions. ESMs can help policy makers understand the implications of different energy policies in terms of energy security, economic performance, and environmental impacts. These models can also be used to identify the most cost-effective solutions to energy challenges, or to compare the benefits and costs of different energy-environmental policies.

1.2. Knowledge Gap

Every ESM has been developed to answer very specific questions due to the complexity of the energy system and limited computational power. As a result, each model comes with specific capabilities and shortcomings.

A large and growing body of literature has listed and classified ESMs with different aims and scopes. Connolly et al. have provided a comprehensive overview intended to identify suitable ESMs to address issues related to renewable energy integration [14]. Similarly, Bhattacharyya et al. have compared energy models to identify the most suitable model for developing countries [15]. Aiming to find the prevalent modeling approaches for the U.K., Hall et al. have classified and compared ESMs based on their structure, technological detail, and mathematical approach [16]. To find trends in energy system modeling, Lopion et al. have reviewed ESMs in a temporal manner [17]. Some reviews have emphasized the role of policy questions and the corresponding modeling challenges. By grouping energy models in four categories, Pfenniger et al. have examined the policy challenges they face in each paradigm [18]. Horschig et al. have reviewed ESMs to provide a framework for identifying a suitable methodology for the evaluation of renewable energy policies [19]. Likewise, Savvidis et al. have identified the gaps between low-carbon energy policy challenges and modeling capabilities with a focus on electricity market models [20]. Some authors such as Ringkjøb et al. have classified ESMs with a focus on the electricity sector [21], while others such as Li et al. have reviewed socio-technical models emphasizing on societal dynamics [22].

There are several current and future low-carbon emitting energy system modeling challenges. The increasing share of Variable Renewable Energy Sources (VRES) requires ESMs to incorporate high temporal resolutions. There is a need to model Carbon Dioxide Removals (CDR) by means of carbon capture and storage (CCS), bioenergy with carbon capture and storage (BECCS), and direct air carbon capture and storage (DACCS). Moreover, ESMs should be aligned with the rapid technological development through introducing new low-carbon technologies or high technological and efficiency learning rates. Further, the higher involvement of human stakeholders in the energy system transition highlights the necessity of alternative modeling methods such as Agent-Based Models (ABMs). Additionally, investigating the impact of the energy transition policies on the macroeconomic state (e.g., economic growth and employment), entails using computable general equilibrium (CGE) models. Therefore, there is a need for a more in-depth integrated analysis, i.e., analyzing the whole energy system consisting of technical, microeconomic, and macroeconomic aspects.

However, current ESMs lack specific capabilities for adequately addressing low-carbon emitting energy system changes that can cause debated conclusions. For instance, one study finds that there is no feasible way to achieve a 100% renewable power system by 2050 [23], while another study claims a 100% renewable EU power system scenario with 30% higher annual costs [24]. Connolly et al. suggest that a 100% renewable EU energy system can be achieved by 2050 with 12% higher annual energy system costs [25], while neglecting significant parameters such as the electricity grid costs, location of renewables, key technological detail, and flexible electricity demand. Brouwer et al. provide a detailed analysis of the West European power sector with high shares of renewables, while neglecting the heat and transport sectors [26]. Brown et al. analyze the cross-sectoral and cross-border integration of renewables in Europe, while assuming no national transmission costs, limited efficiency measures, and limited technology options [27]. Social aspects of the energy system transition are usually neglected in ESMs, although some studies analyze actors' behavior in the energy system on the demand side; for instance, they investigate the thermal demand transition [28] or the adaptation of efficiency measures of households [29]. Analyzing each of the major changes in the energy system can be challenging for conventional ESMs as they need further capabilities such as fine technological detail, high temporal and spatial resolutions, and the presence of stakeholders' behavior.

So far, many questions are typically addressed by detailed models of the electric power sector with a high level of technological and temporal resolution but without considering the rest of the energy system. However, these issues affect other energy sectors as well. On the other hand, typical system-wide energy models cannot quickly introduce such levels of detail without becoming excessively complex. Therefore, there is a need for either improving the performance of the current energy-system models or coupling ESMs with more detailed sectoral energy models and other ad-hoc auxiliary tools for the development of these various models.

Current single models can be developed and/or extended by incorporating additional capabilities up to acceptable computational limits. Considering the limitations, the modeler makes choices and/or trade-offs on extensions to the model. The computational limitation can be addressed either by hardware or software development. Hardware development follows exponential growth and relates to improvements in the number of transistors, clock frequency, and power consumption of processors. Software development refers to solver-related developments, model reduction, and clustering methods that can be applied to temporal resolution, spatial resolution, and technological detail. Depending on the research questions to be answered, energy system modelers reduce or coarsen the resolution of the model to provide an answer in an adequate timeframe.

An alternative approach to overcome the limitations of single-model development is to form a modeling suite by combining different models. Model linking can be done between any set of desired models to enhance modeling capabilities. Among those, two types of energy model linking are more frequent in the literature: (1) Linking Bottom-Up (BU) and Top-Down (TD) models, such as optimization energy system models (OESMs) linked with CGE models, and (2) linking two BU models, such as OESMs linked with energy market models (e.g., unit commitment or power dispatch models). Although linking models provides additional modeling capabilities, it comes with particular challenges, such as the identification of connection points in soft-linking, convergent solutions in soft-linking, and mathematical formulation for integrated linking. However, linking models can be resource intensive as it requires the knowledge of different modeling frameworks. Furthermore, each model has its own set of assumptions and methodologies, making it complicated to maintain the harmonization of modeling assumptions in all linking steps. The lack of harmonization in assumptions may result in inconsistent results from linked models. Although this process seems straightforward, it is a puzzling procedure as ESMs are moderately complex. Therefore, having an overview of different energy models and their capabilities is essential to provide the desired modeling suite.

In summary, current Energy System Models (ESMs) do not have the ability to accurately address the challenges of transitioning to a more sustainable energy system. They can be inefficient and fail to account for the full range of energy sources, technologies, and policies available. They also often fail to consider the long-term costs of energy use, the impacts of climate change, and the potential of energy efficiency and renewable energy sources considering short-term operational constraints.

1.3. Research objective and questions

The objective of this research program is to provide insights into the linkages and interactions of future integrated energy systems with increasing shares of intermittent renewables in the electricity supply. More specifically, the main objective is to provide detailed and quantitative insights into the transition pathways towards future integrated energy systems at the (inter)national level, based on detailed representations of the full energy system, which includes the various parts of the energy system at different geographical scales, taking into account technical, microeconomic, and macroeconomic aspects and using the information on, for example, flexible technologies, the potential for energy efficiency, and demand response.

The insights this research provides allows for a better understanding of future market developments, knowledge about promising flexibility options (both technologies and options such as demand side response), and the drivers and barriers for these options. It also helps to identify the role of different energy sources, technologies (e.g., gas, coal, and CCS), and the crucial role of infrastructure (e.g., hydrogen and heat pipelines and electricity grids) within the transition itself because we explicitly consider the transition path and not only focus on the long-term low-carbon emitting energy system.

This approach helps policymakers, businesses, and other stakeholders to make better-informed decisions on policies, regulations, and investments such as market design, energy infrastructure, R&D, and technology choice.

The overall objective of the present research can be summarized as follow:

"Providing quantitative insights into energy transition pathways using a framework approach which links bottom-up and top-down energy and economy models, covers the whole demand, supply, infrastructure and trade of energy, has a low entry-barrier, and features advanced capabilities, such as, wide range of flexibility options and hourly temporal resolution, tailored to answer future policy questions."

This overall objective can be disaggregated into three cross-cutting research questions:

1. To what extent can we improve the methodology, technological and temporal resolution, and capabilities of national energy system models to address future policy questions?
2. What are the implications of these model improvements on required data at specific resolutions and how does data availability restrain such improvements?
3. How can advanced modeling capabilities and resolutions inform Dutch energy transition scenarios with respect to environmental policies, direction and timing of investments, and its impact on the economy?

Each research chapter focuses on one, two, or three of the above questions (Table 1).

Table 1. Overview of answered research questions in each chapter

	Chapter 2	Chapter 3	Chapter 4	Chapter 5	Chapter 6	Chapter 7
RQ 1						
RQ 2						
RQ 3						

1.4. General approach

New about the current approach is developing an energy modeling framework that includes a detailed representation of all critical aspects of the different parts of the energy system at different geographical scales, from local distribution grids to international electricity markets (Figure 1). This framework combines optimization and simulation methodologies while considering regional spatial features of the energy transition and linking with the macroeconomic behavior of the national economy.

At the core of this framework, we develop an integrated energy system model that includes demand, supply, infrastructure, and trade of energy. Moreover, all the relevant interactions within the integrated energy system are taken into account, such as, for example, the interaction between decentralized solar-PV and possibly storage at the household level and increasing interconnections, the effect of changing peak capacity gas demand from gas-fired power plants which provide flexibility on the need for gas infrastructure and the potential of heat demand in industry as an option to accommodate surplus electricity production from wind and solar-PV. Last, the transition itself is explicitly considered, which has only been done in a limited number of studies. While similar initiatives are being developed abroad, such an approach has so far been lacking within the Netherlands. Furthermore, we expand the framework by linking the developed core model with a general equilibrium model to ensure consistency between the energy system policies and the economy.

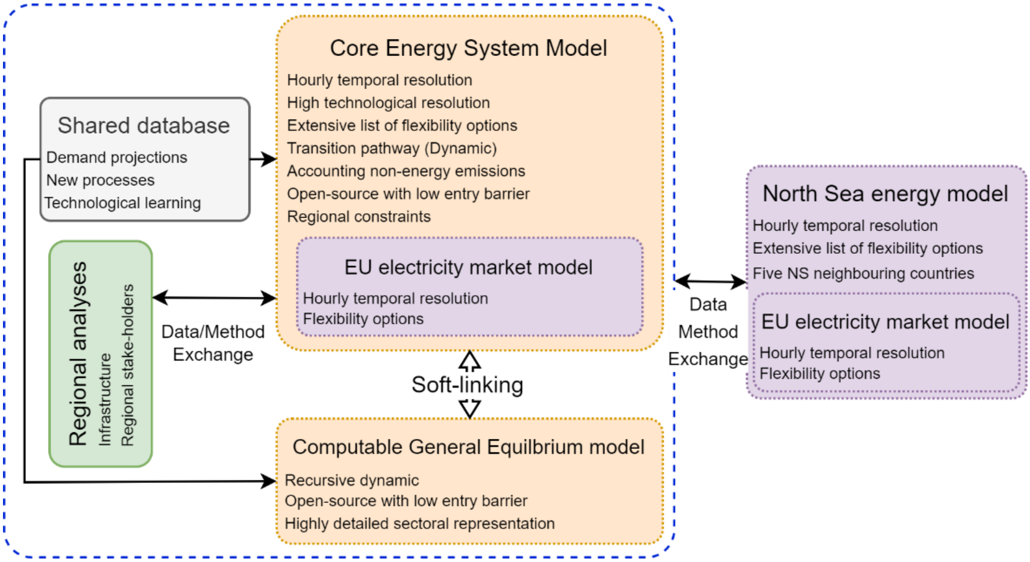

Figure 1. The general approach of this study with its components and relations.
Box colors: Lime: Regional scale; Orange: National scale; Purple: Transnational scale

In addition, the present research has been conducted in collaboration with experts from partner institutes and other Ph.D. students (See Box 1). Partner institutes assisted us with developing the methodology and obtaining required data. Moreover, the core developed model has been expanded to the North Sea region to find the role of offshore wind regions in minimizing energy transition costs.

Box 1: The ESTRAC and ENSYSTA projects and the user interface

The model development is part of a modeling suite that includes optimization, simulation, and general equilibrium methodologies in different geographical scales. The national core optimization model is developed by Amirhossein Fattahi (i.e., the author of this thesis) and Manuel Sánchez Dieguez. Furthermore, the regional aspect is studied by Ph.D. student Somadutta Sahoo of the ESTRAC project; and the outcomes are reflected in the national core model design. Moreover, the model development is expanded to North Sea countries by Ph.D. student Rafael Martinez Gordon of the ENSYSTRA project. Furthermore, the national model is linked with a general equilibrium model to account for macroeconomic interactions of energy transition policies. The summary of our approach is depicted in Figure 2.

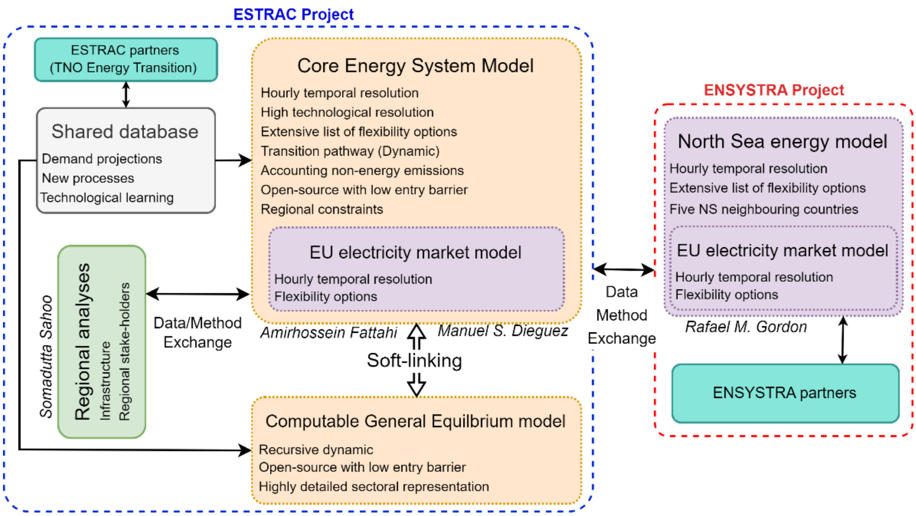

Figure 2. The general approach of this study with its components and relations.
Box colors: Lime: Regional scale; Orange: National scale; Purple: Transnational scale; Cyan: Project partners

The ESTRAC project

This study is part of the ESTRAC-IESA project (Energy System TRAnsition Center - Integrated Energy System Analysis), directed by the New Energy Coalition (NEC) (finance code: 656039). The ESTRAC project was a joint effort between NEC, University of Groningen (RUG), Hanzehogeschool Groningen, NAM, GASUNIE, GASTERRA, EBN, and TNO Energy and Material Transition (formerly ECN and TNO). The primary financial backing for the project came from NAM, GASUNIE, GASTERRA, and EBN.

This project involved three Ph.D. researchers who developed ESMs focused on different geographical resolutions. On the one hand, one Ph.D. researcher, Somadutta Sahoo, studied the regional aspects of the ESMs in collaboration with Spatial Sciences faculty of RUG. On the other hand, two Ph.D. researchers, Amirhossein Fattahi and Manuel Sánchez Dieguez, investigated the project at the national and international scale in close collaboration with TNO Energy and Materials Transition.

Since the objective of the latter two Ph.D. researchers involved developing a state-of-the-art ESM, they conducted their study in close collaboration. Therefore, the chapters involving the IESA-Opt model development (i.e., three, four, and five) are shared between the two mentioned Ph.D. researchers. As a result, these shared chapters are repeated in both theses. Figure 3 summarizes the Ph.D. deliverables (theses and software) the two Ph.D. students developed.

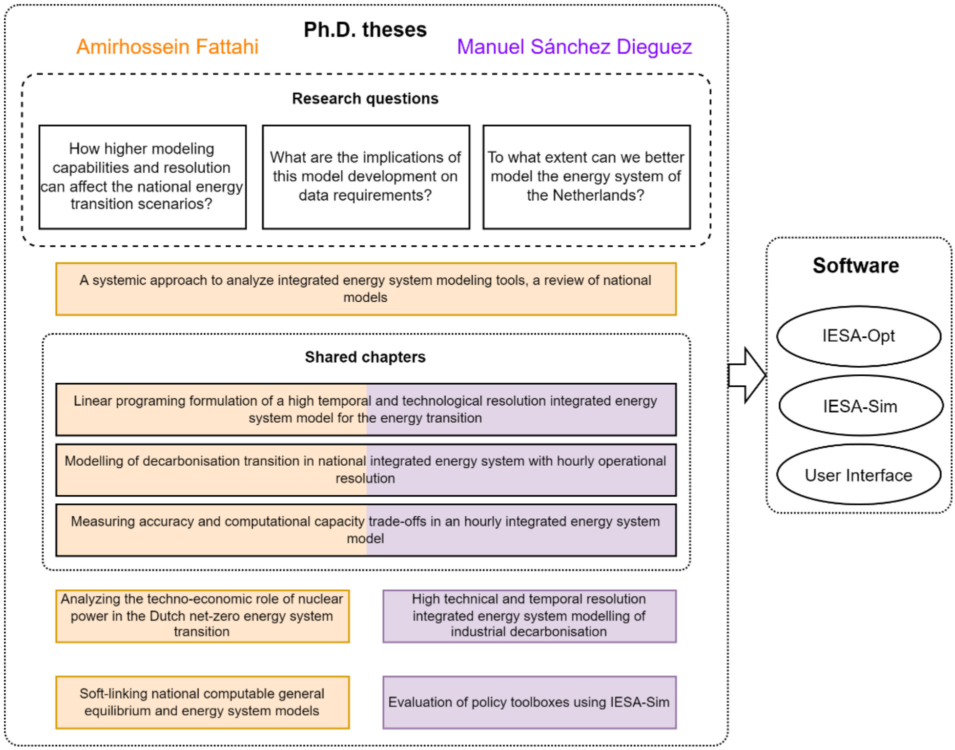

Figure 3. Overview of the Ph.D. deliverables (theses and software) of the ESTRAC project at the national and international scale.

ENSYSTRA project

The ENSYSTRA (ENergy SYStems in TRAnsition Innovative Training Network) project aims to make the crucial connections between different methods and modelling approaches in energy system analysis, technology development, actor behavior and in the interplay with markets and regulatory frameworks with the focus on the North Sea region. It comprises thirty-one partners including RUG and TNO Energy and Material Transition. We had a close collaboration with this project by expanding the IESA framework to the North Sea region and developing the IESA-NS energy system model. From the ENSYSTRA project, we collaborate closely with Ph.D. student Rafael Martinez Gordon.

User interface

Apart from the developed models (IESA-Opt, IESA-Sim, and IESA-NS) and methodology (soft-linking models), we also developed a user interface (UI) that visualizes the results of models in an interactive way. The UI reads the output of the models and instantly visualizes major key indicators of the energy transition together with major output parameters, such as energy mix, activity mix, system costs, LCOEs, supply and demand of energy in each activity, hourly flexibility analyses, 3D profiles of resources and technologies, price duration curves, and the Sankey diagram. The produced graphs and diagrams are interactive, which gives the user the ability to analyze the modeling results in depth and save snapshots for reporting purposes. This UI is written in R and it can be deployed online in the html format.

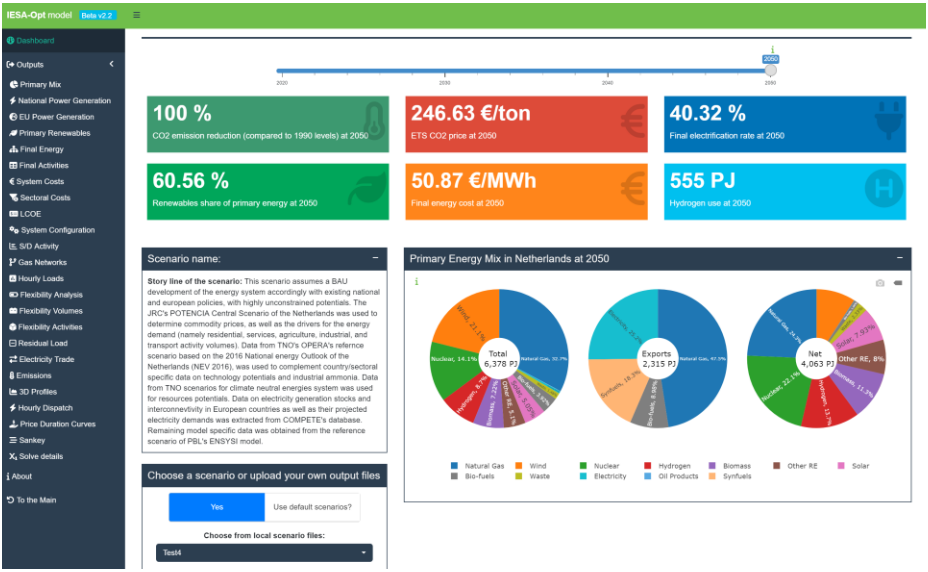

Figure 4. The dashboard of the IESA framework online UI.
This UI was developed in parallel to the IESA framework and acts as a model development, visualization, and dissemination environment. User can see varied set of graphs and diagrams by clicking on each tab on the left side.

1.5. Outline of the dissertation

The proposed approach consists of several activities, including literature review, model development, calibration, analyses, and links that are presented in Figure 5. First, a modeling framework, IESA, is proposed in Chapter 2 by reviewing the latest state of the literature on national energy system models. Then, in Chapters 3 to 5, the core energy system model, IESA-Opt, is developed, calibrated, and documented. Later, the capabilities of the IESA-Opt model are demonstrated by analyzing the role of nuclear power in the Dutch energy transition. Finally, the IESA modeling framework is developed further by soft-linking the core IESA-Opt model with a macroeconomic CGE model.

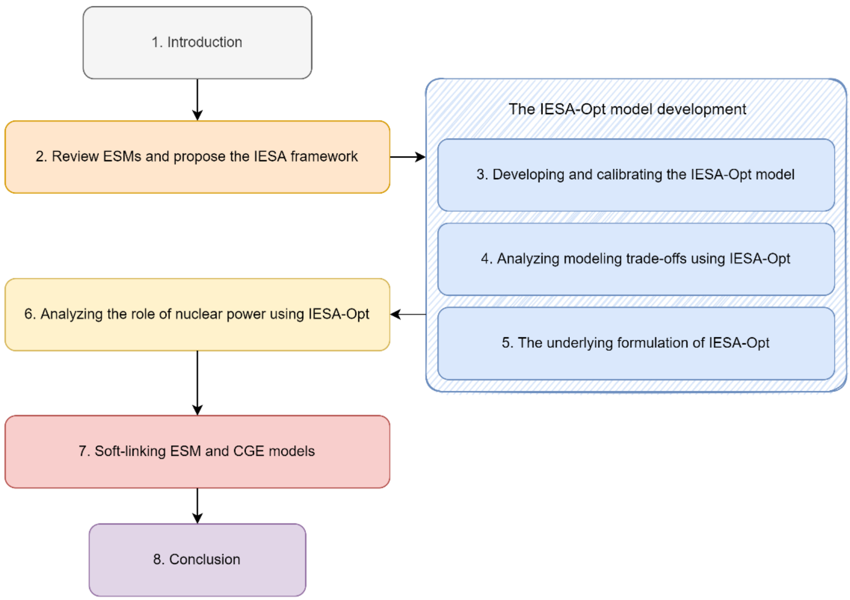

Figure 5. The overall schematic of the thesis chapters.

Chapter 2: A systemic approach to analyze integrated energy system modeling tools, a review of national models

In the second chapter, an overview is made of the current research and knowledge on integrated energy system models aiming to address the shortcomings of current ESMs, considering current and future low-carbon energy system modeling challenges.

This chapter describes current and future low-carbon energy system modeling challenges. Then, based on low-carbon energy system modeling challenges, this chapter identifies required modeling capabilities, such as the need for hourly temporal resolution, sectoral coupling technologies (e.g., P2X), technological learning, flexibility and storage technologies, human behavior, cross-border trade, and linking with the market and macroeconomic models. The required capabilities are then translated into Multi-Criteria Analysis (MCA) assessment criteria. Finally, potential model development solutions are discussed, and the IESA modeling suit is proposed as a model-linking solution to address the energy modeling challenges (Figure 6).

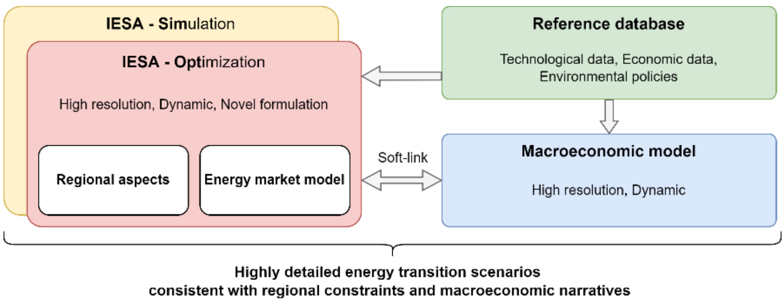

Figure 6. The schematic of the IESA modeling framework

Chapter 3: Linear programing formulation of a high temporal and technological resolution integrated energy system model for the energy transition

This chapter documents the underlying formulation of the IESA-Opt model in detail. It is known from the literature that models with a broad technological representation of energy systems can hardly adopt hourly resolutions to study the energy transition towards low-carbon technologies due to the extended problem size. This compromises the model's ability to address the challenges of variable renewable energy sources and the cost-effectiveness of cross-sectoral flexibility options. This methodology presents a linear program model formulation that simultaneously adopts different temporal representations for different parts of the problem to overcome this issue. For instance, all electricity activities and their infrastructure representation require hourly constraints to replicate system feasibility better. The operation of gaseous networks is settled out with daily constraints. The balancing of the other activities of the system is represented with yearly constraints. Furthermore, the methodology adopts an hourly formulation to represent in detail six cross-sectoral flexibility archetypes: heat and power cogeneration, demand shedding, demand response, storage, smart charging, and electric vehicles. As a result, the model can successfully solve the transition problem from 2020 to 2050 in 5-year intervals with more than 700 technologies and 140 activities (including the electricity dispatch of the Netherlands and 20 European nodes) in less than 6 hours with a standard computer.

Chapter 4: Modelling of decarbonisation transition in national integrated energy system with hourly operational resolution

Following up on the proposed modeling framework of chapter 2, the methodology for energy system integration analysis has been further improved by developing the core optimization model of the IESA framework. The integrated energy system analysis optimization model, IESA-Opt, facilitates the harmonized and combined use of (future) simulation, regional, and macroeconomic-focused analyses as part of the IESA modeling framework for the Netherlands. This linear programming (LP) model simultaneously solves the short-term hourly operation and long-term 5-year interval planning problems from

2020 to 2050 (with the possibility of extending the time horizon). Furthermore, the model includes multi-year techno-economic data of more than 700 technologies in all sectors for both energy transformations (i.e., electricity, refineries, heat, hydrogen, gas, and biomass) and final demand (i.e., residential, services, agriculture, transport, and industry). In this rich technological representation, cross-sectoral technologies are included, such as P2Heat, P2Gas, P2Hydrogen, P2Liquids, P2Mobility, and V2Grid, as well as the corresponding descriptions of their flexible hourly operation. Exogenous technological learning, efficiency improvements, and decommissioning and retrofitting parameters are also included in the formulation. To model the implications of hourly import and export of electricity on the Dutch energy system, IESA-Opt comprises an hourly electricity dispatch of EU countries with 20 nodes, each with their own hourly load, specific hydro storage capacity, onshore wind, offshore wind, and solar profiles. In addition to GHG emissions related to the energy system (divided into emissions within and outside the Emissions Trading Scheme (ETS)), the model also considers the emissions from non-energy sources, such as enteric fermentation, fertilizers, manure management, and refrigeration fluids. To address the network buffer capacity, IESA-Opt represents the operation of gaseous networks [17] based on a daily balance dispatch [18]. The energy infrastructure is modeled in ten networks for different voltage levels of electricity and different pressure levels of natural gas, hydrogen, and CCUS, as well as for district heating distribution.

One of the objectives of developing IESA-Opt is to provide a low entry barrier (i.e., transparent) model that requires no upfront financial investment (to purchase specialized licenses) for academic research. In addition, owing to the enormous size of the optimization problem, there is a need for efficient computing software that is commercially available. Therefore, two commercial software packages with a free academic license are selected to maximize the computational efficiency and accessibility of the model. IESA-Opt is implemented in the commercial AIMMS software [19], which uses an algebraic modeling language, such as GAMS, AMPL, and MPL. The GUROBI mathematical optimization solver [20] is used to solve the LP problem in parallel central processing unit cores. Moreover, to expand the accessibility of the model and its results, the results of the model are visualized using a web-based user interface that is realized in the R programming language [21]. The model's source code and database are available online through its web user interface [22].

Chapter 5: Measuring accuracy and computational capacity trade-offs in an hourly integrated energy system model

The capabilities of the developed IESA-Opt model are further analyzed in this chapter. Four of the modeling capabilities of IESA-Opt are discussed in this chapter. First, the transitional scope (i.e., multi-period solutions) allows the incorporation of multi-period factors, such as technological lifetime, decommissioning, technological learning, and efficiency improvements, in energy models. At the expense of a higher computational load, the transitional model enables pathway conclusions to be drawn, such as optimal periods to invest in specific technologies.

Second, integrating European electricity dispatch with the national ESM provides cross-border trade flexibility at hourly time steps. Several national ESMs represent the power generation sector of neighboring countries by including their dispatch decisions (e.g., [1]). In highly interconnected systems (e.g., northwest Europe), neglecting cross-border trade or having a static representation of cross-border flows can lead to inaccurate technology portfolios and system cost estimates [2].

Third, a detailed description of flexibility options at hourly time steps is necessary for modeling the integration of high shares of VRES [3]. Moreover, modeling all energy system flexibility options such as P2Heat, P2Mobility, P2Liquid, and P2Gas is necessary to estimate energy storage needs [17] accurately. IESA-Opt includes a detailed list of flexibility options divided into six main groups: flexible CHPs (11 technologies), shedding (6 technologies), demand response (2 technologies), storage (3 technologies), smart charging (3 technologies), and V2Grid (1 technology).

Finally, the inclusion of infrastructural constraints allows the system to account for infrastructure development costs. The existing infrastructure is not fully compatible with a low-carbon energy system mainly due to the lack of CCUS and hydrogen networks [4]. All four capabilities can have major effects on the long-term planning of the energy system.

This chapter measures the cost of increasing resolution in each modeling capability in terms of computational time and accuracy of energy system modeling indicators, notably system costs, emission prices, electricity generation, and import and export levels.

Chapter 6: Analyzing the techno-economic role of nuclear power in the Dutch net-zero energy system transition

In this chapter we identify four major methodological shortcomings and knowledge gaps of the (Dutch) literature on the role of nuclear power in the future (climate-neutral) energy systems: (1) The system-wide implications of nuclear power in a transition to a net-zero energy system is barely discussed. These implications refer not only to economic feasibility of this technology, but also its impact on other energy sectors, system costs, and flexibility demand and supply. Therefore, integrated energy modeling tools are required to compute the system-wide influence of techno-economic decisions [5]. (2) Moreover, there is a great controversy on the cost data of nuclear and VRES. The range of cost data for these technologies is relatively wide [6], which can significantly affect the cost-optimal power generation mix. (3) Furthermore, small modular reactors (SMRs) as flexible nuclear technologies are not included in the reviewed studies. However, they are expected to play an active role in providing flexibility to the power system [7]. (4) Finally, neglecting cross-border electricity trade can overestimate electricity prices by 40% [8].

Moreover, it can significantly affect the optimal electricity import and export levels, and, hence, the power generation mix. Therefore, assumptions regarding the cross-border electricity trade can highly affect the investment and operation of nuclear power.

This chapter demonstrates the IESA-Opt model's capabilities to analyze the role of nuclear power in the Dutch energy transition. This chapter is framed around four themes, corresponding to the four identified knowledge gaps: (1) the system-wide impact of nuclear power in an integrated energy system, (2) the role of nuclear cost uncertainties on cost-effective nuclear investment decisions, (3) the role of SMRs as a flexible generation option on cost-effective nuclear investment decisions, and (4) the impact of the cross-border electricity trade on economic nuclear investment decisions.

Moreover, this chapter modifies the model in two directions: improving the objective function definition and adjusting the cross-border electricity trade assumptions.

Chapter 7: Soft-linking a national computable general equilibrium (ThreeME) model with a detailed energy system model (IESA-Opt)

Providing an effective climate mitigation policy advice requires insights that take both top-down (TD) and bottom-up (BU) effects of such an advice into account. Such an approach has been used to present an in-depth analysis of global decarbonization scenarios in several studies, such as the climate change report of IPCC AR6 [9], the global energy and climate outlook of JRC [10], and the World Energy Outlook of IEA [11].

Due to the growing national policy-driven demand for analyzing socially optimal energy transition pathways [12] and the lack of scientific literature on linking details, there is a need for a transparent national model linking process and its underlying assumptions. Moreover, the detail level of soft-linked models can be improved by using state-of-the-art TD and BU models.

The proposed IESA framework in Chapter 2 is expanded one step further by soft-linking the core IESA-Opt energy system module with a national macroeconomic model. For this purpose, the recently developed open-source ThreeME model [24] is tailored to the IESA framework. Moreover, the impact of the model linking on the modeling results is demonstrated in the case study of the Netherlands. Furthermore, the relevance of each soft-linking feedback parameter on the modeling results is quantified. Finally, the challenges of the proposed soft-linking approach are discussed, and directions for future research are provided.

Chapter 8: Summary and conclusion

Finally, this dissertation will be summarized and concluded by synthesizing our learnings from the previous chapters and reflecting on our findings. In addition, we will determine possible next steps to pursue this approach and research further.

A systemic approach to analyze integrated energy system modeling tools, a review of national models [1]

Abstract

This chapter reviews academic literature focusing on nineteen integrated Energy System Models (ESMs) to (i) identify the capabilities and shortcomings of current ESMs to analyze adequately the transition towards a low-carbon energy system, (ii) assess the performance of the selected models by means of some derived criteria, and (iii) discuss briefly some potential solutions to address the ESM gaps.

This chapter delivers three main outcomes. First, to identify key criteria for analyzing current ESMs, seven current and future low-carbon energy system modeling challenges are described, namely, the increasing need for flexibility, further electrification, emergence of new technologies, technological learning and efficiency improvements, decentralization, macroeconomic interactions, and the role of social behavior in the energy system transition. These criteria are then translated into required modeling capabilities such as the need for hourly temporal resolution, sectoral coupling technologies (e.g. P2X), technological learning, flexibility technologies, stakeholder behavior, cross border trade, and linking with macroeconomic models. Second, a Multi-Criteria Analysis (MCA) is used as a framework to identify modeling gaps while clarifying high modeling

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capabilities in some models such as MARKAL, TIMES, REMix, PRIMES, and METIS. Third, to bridge major energy modeling gaps, two conceptual modeling suites are suggested, based on both optimization and simulation methodologies, in which the integrated ESM is hard-linked with both a regional model and an energy market model and soft-linked with a macroeconomic model.

2.1. Introduction

The long-term energy strategy of the EU is aimed at 80-95% Greenhouse Gas (GHG) emissions reduction by 2050, relative to 1990. Reaching this goal requires a number of key actions intended to make a transition from a conventional energy system to a low-carbon energy system [13]. As a result, low-carbon Energy System Models (ESMs) have been developed to guide decision makers on taking long-term robust policy decisions towards energy system transition. However, every ESM has been developed to answer specific policy questions, due to the complexity of the energy system and limited computational power. As a result, each model comes with specific capabilities and shortcomings.

A large and growing body of literature has listed and classified ESMs with different aims and scopes. Connolly et al. have provided a comprehensive overview intended to identify suitable ESMs to address issues related to renewable energy integration [14]. Similarly, Bhattacharyya et al. have compared energy models to identify the most suitable model for developing countries [15]. Aiming to find the prevalent modeling approaches for the U.K., Hall et al. have classified and compared ESMs based on their structure, technological detail, and mathematical approach [16]. To find trends in energy system modeling, Lopion et al. have reviewed ESMs in a temporal manner [17]. Some reviews have emphasized the role of policy questions and the corresponding modeling challenges. By grouping energy models in four categories, Pfenniger et al. have examined the policy challenges they face in each paradigm [18]. Horschig et al. have reviewed ESMs to provide a framework for identifying a suitable methodology for the evaluation of renewable energy policies [19]. Likewise, Savvidis et al. have identified the gaps between low-carbon energy policy challenges and modeling capabilities with a focus on electricity market models [20]. Some authors such as Ringkjøb et al. have classified ESMs with a focus on the electricity sector [21], while others such as Li et al. have reviewed socio-technical models emphasizing on societal dynamics [22].

The increasing share of Variable Renewable Energy Sources (VRES) caused the low-carbon energy system transition to face several major challenges, such as the increasing need for flexibility, further electrification, emergence of new technologies, technological learning, efficiency improvements, decentralization, macroeconomic interactions, and the higher involvement of human stakeholders in the energy system transition. Additionally, some policy questions at the macro level, such as the impact of the energy transition on the macroeconomic performance (e.g. economic growth and employment), require more in-depth integrated analysis, i.e. analyzing the whole energy system consisting of technical, microeconomic, and macroeconomic aspects.

However, current ESMs lack specific capabilities for adequately addressing low-carbon energy system changes that can cause debated conclusions. For instance, one study finds that there is no feasible way to achieve a 100% renewable power system by 2050 [23], while another study claims a 100% renewable EU power system scenario with 30% higher annual costs [24]. Connolly et al. suggest that a 100% renewable EU energy system can be achieved by 2050 with 12% higher annual energy system costs [25], while neglecting significant parameters such as the electricity grid costs, location of renewables, key technological detail, and flexible electricity demand. Brouwer et al. provide a detailed analysis of the West European power sector with high shares of renewables, while neglecting the heat and transport sectors [26]. Brown et al. analyze the cross-sectoral and cross-border integration of renewables in Europe, while assuming no national transmission costs, limited efficiency measures, and limited technology options [27]. Social aspects of the energy system transition are usually neglected in ESMs, although some studies analyze actors' behavior in the energy system on the demand side; for instance, they investigate the thermal demand transition [28] or the adaptation of efficiency measures of households [29]. Analyzing each of the major changes in the energy system can be challenging for conventional ESMs as they need further capabilities such as fine technological detail, high temporal and spatial resolutions, and the presence of stakeholders' behavior.

This study concentrates on the energy modeling challenges which result from the increasing share of VRES, complexity, and system integration although the transition towards a decarbonized energy system can involve other policies such as the higher energy efficiency and change in energy demand, the use of nuclear power supply, and using Carbon Capture Utilization and Storage (CCUS) technologies. Moreover, due to the diversity of ESMs, two major limitations will be imposed on this review in order to keep it manageable. First, this research chapter focuses on energy models at the national level. Therefore, reviewed models are designed for national analysis or they can be used for national assessments (e.g. PRIMES model). Second, reviewed models cover the whole energy system including all the energy sectors.

The overarching research question of this study is "What are the potential solutions to address the shortcomings of current ESMs considering current and future low-carbon energy system modeling challenges?". To answer this question, first, the current and future low-carbon energy system modeling challenges are described. Based on low-carbon energy system modeling challenges, this review identifies required modeling capabilities, such as the need for hourly temporal resolution, sectoral coupling technologies (i.e. P2X), technological learning, flexibility and storage technologies, human behavior, cross border trade, and linking with market and macroeconomic models. The required capabilities are then translated into assessment criteria to be used in Multi-Criteria Analysis (MCA). Finally, potential model development solutions are discussed and a modeling suit is proposed as a model-linking solution to address the energy modeling challenges.

2.2. Method

Seven major low-carbon energy system modeling challenges were identified and described in Section 3. The challenges were translated into a number of required energy system modeling capabilities and criteria to be used in later sections.

Nineteen models were selected from other reviews in the literature such as Connolly et al. [14] and Hall et al. [16]. Primary inclusion criteria for the selected models (see Table 2) were (1) being used at national level and (2) covering the whole energy system (i.e. integrated energy system models). All the presented information from the selected models was gathered from officially published documents that may be incomplete or outdated (notably when this chapter is published), as models are continuously further developed. For each model, a brief description was provided in the Appendix section.

Model	Developer	Model	Developer
DynEMo	UCL [30]	**METIS**	Artelys [31]
E4Cast	ABARE	**NEMS**	EIA
EnergyPLAN	Aalborg University [32]	**OPERA**	ECN [33]
ENSYSI	PBL	**OSeMOSYS**	KTH, UCL [34]
ESME	ETI [35]	**POLES**	Enerdata [36]
ETM	Quintel Intelligence	**PRIMES**	NTUA [37]
IKARUS	Research Center Jülich [38]	**REMix**	DLR [39]r
IWES	Imperial College London	**SimREN**	ISUSI
LEAP	Stockholm Environmental Institute [40]	**STREAM**	Ea Energy Analyses [41]
TIMES	IEA [42]		

Table 2, The reviewed models and their corresponding developers

Multi-Criteria Analysis methodology was used as a transparent framework to analyze complex ESMs from different perspectives. MCA is a methodology to analyze complex choices (i.e. various criteria, objectives, and indicators), which has been used extensively for analyzing energy transition policies [43]. The major advantage of MCA is that it provides a rational structure of complex alternatives that presents substantial elements for identifying the desired choice [44]. Although MCA may have different purposes, we were particularly interested in: first, breaking down complicated energy models into key criteria; and second, identifying the importance or relative weight of each criterion for each alternative. Models were ranked in tables based on known criteria, but this did not mean one model was superior to others. Therefore, the intention was not to “compare” models but to identify modeling capabilities and "gaps" that was used for structuring the low-carbon energy system modeling framework.

Based on the identified modeling gaps, a conceptual modeling suite was proposed to address future low-carbon energy system modeling challenges. The proposed modeling suite included a core integrated energy system model that was hard-linked with a regional model and soft-linked with both an energy market model and a macroeconomic model.

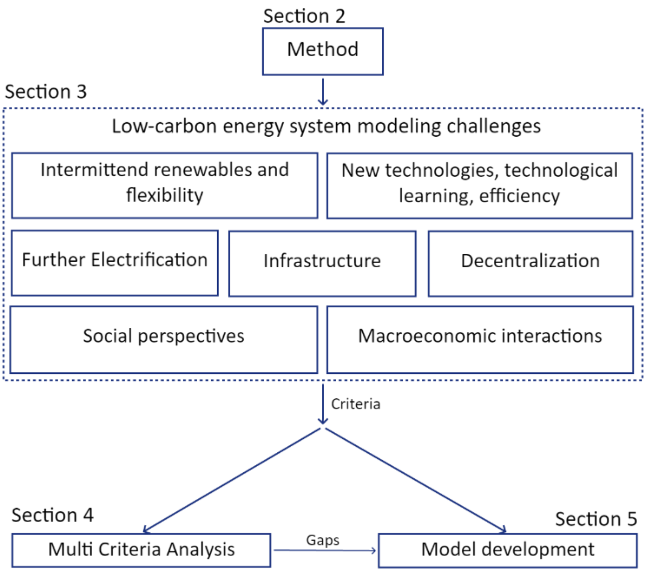

Figure 7, The structure of this study

2.3. Low-carbon energy system modeling challenges

Energy policies are designed to meet three key objectives of the energy system which are providing energy reliability (i.e. supply security), affordability (i.e. economics and job creation), and sustainability (i.e. environment and climate). With the aim of reviewing electricity market models, Savvidis et. al. [20] cluster twelve energy policy questions as a basis to quantify the gap between models and policy questions. Based on the literature and experts' opinions, we divide energy modeling related policy questions into four categories as follows:

1. Technical questions such as a lack of insights in higher share of intermittent renewables, role of new technologies, and further electrification of the energy system.
2. Microeconomic questions such as a lack of insights in decentralization, human behavior, and liberalized energy markets.

3. Macroeconomic questions such as a lack of insights in economic growth and jobs due to the energy transition.
4. The mix of the above such as lack of insights on the effect of new technologies on energy markets and jobs.

Providing a solution for each policy inquiry can be a challenge for energy system modeling. These challenges can alter the choice of modeling methodology and parameters. In this section, energy modeling challenges and the corresponding modeling parameters are described.

2.3.1. **Intermittent renewables and flexibility**

Some sources of renewable energy such as wind and solar energies have an intermittent characteristic i.e. they are (highly) variable and less predictable [45]. The power generation from intermittent renewables is directly dependent on weather conditions [46]. As wind and solar power generation technologies are becoming more competitive, it is expected that wind and solar power generation will take up to 30% and 20% of the EU's electricity demand by 2030, respectively. Hence, a high share of intermittent renewables in the electricity generation sector is imminent.

Variability

Technically, the power system needs to be in balance at all temporal instances and geographical locations. Therefore, the electricity sector should be structured in a way to ensure the balancing of demand and supply. The higher share of intermittent renewables (mainly from wind and solar sources) entails variability on the power system balance [47]. Solutions to deal with power balance variabilities are called flexibility options (FOs) as they provide flexibility to the power system against the variable and uncertain residual load profiles.

Traditionally, conventional power supplies and grid ancillary services were primary sources of flexibility. However, the power system needs further FOs as the share of intermittent renewables in the power generation increases while the share of conventional power supplies - i.e. notably dispatchable gas-fired power plants - decreases. Several review papers can be used as a starting point of FOs' literature review ([48],[49]). An extensive review of different FOs is provided by Lund et al. [50] who list FOs as Demand Side Management (DSM), storage, power to X, electricity market designs, conventional supply, grid ancillary services, and infrastructure (e.g. smart grids and microgrids). Further, Sijm et al. [51] investigate FOs by suggesting three causes of the demand for flexibility as the variability of the residual load, the uncertainty of the residual load, and congestion of the grid. Michaelis et al. [52] divide FOs based on the residual load in three groups, which are downward, upward, and shifting flexibility. Due to high detail and complications regarding each FO, some studies focus mainly on one or a few technologies. To name a few examples: Blanco et al. investigate the cost-optimal share of power to methane in the EU energy transition [53]. The potential of power to heat and power to ammonia in the Dutch energy system is investigated by Hers et al. (Hers, Afman, Cherif, & Rooijers, 2015) and ISPT (ISPT, 2017), respectively. Some other studies follow an integrated approach that includes several FOs in different sectors; however, they have to make several assumptions as the computational capacity is limited.

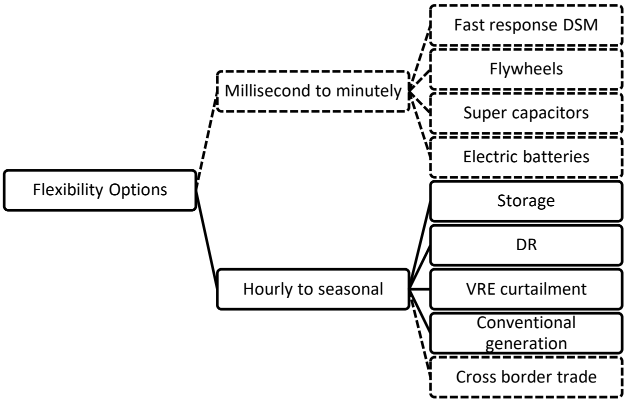

Figure 8, Flexibility options classified by their temporal scale

Note: Dashed options are usually excluded from integrated national energy models.

Flexibility options can be divided into five main groups, i.e. storage, DR, VRE curtailment, conventional generation, and cross border trade. Instead of analyzing the pros and cons of each option, we are interested to identify key energy modeling issues regarding each flexibility option.

Storage

From a temporal perspective, storage FOs can be divided into daily and seasonal storage options. On the one hand, solid state and flow batteries, such as Li-Ion, Ni-Cd, NAS, ICB, VRB, and ZnBr batteries, provide high ramp rate with limited capacity, which is suitable for diurnal power storage. Modeling these batteries requires the diurnal temporal resolution, which can be in different forms such as Hourly Temporal Resolution (HTR) or hourly time-slices (i.e. grouping hours featuring similar characteristics). Improvements in temporal resolution can have a significant impact on modeling results considering the high share of intermittent renewables (e.g. see [54],[55]). On the supply side, the uncertainty regarding weather forecasts needs to be implemented in the model as weather conditions have a significant impact on intermittent renewables' generation (e.g. see [56],[57]). On the other hand, technology options, such as Pumped-Hydro Energy Storage (PHES), Thermal Energy Storage (TES), Large-Scale Hydrogen Storage (LSHS), and Compressed Air Energy Storage (CAES), provide huge capacities that makes them suitable for seasonal energy storage. Modeling seasonal storage options requires the inclusion of Chronological Order (ChO) of the temporal parameter together with a fine temporal resolution as the chronological order of time from summer to winter (and vice versa) determines the charge/discharge of seasonal storage options.

Demand Response

DR refers to a set of schemes to shift the demand in a certain time period (e.g. an hour) to another time period of the day, week, or month, either forward or backward. Currently electricity comprises around 22% of EU final energy consumption. Power to X (P2X) technology options can provide further DR potentials by linking energy sectors and energy carriers together through converting electricity to other forms of energy, services, or products. In its latest report, the World Energy Council of Germany suggests that P2X will be a key element for the transition to the low-carbon energy system. Due to high detail and complications regarding each technology option, several studies focus mainly on one or a few options. At EU level, Blanco et. al. investigates the cost-optimal share of P2G in the EU energy transition. At the national level, the potential of P2Heat and P2Ammonia in the Dutch energy system is investigated.

There is a huge potential for demand response in the built environment sector as it is responsible for 40% of energy consumption and 36% of CO2 emissions in the EU. While individuals can passively participate in either price-based[2] or incentive-based[3] demand response schemes, proactive participation of consumers can increase market efficiency and reduce price volatility [58]. As heating demand represents around 80% of EU average household energy consumption, the DR potential can be realized by coupling electricity and heat demands. DR in the built environment can consist of three main components including P2Heat technologies (e.g. heat pumps and electric boilers), storage (e.g. thermal tank storage and thermally activate building), and smart controllers (that consider market participation, consumer behavior and weather forecast).

As P2X technology options bridge two different energy sectors or carriers, analysis of these options requires multi-sectoral modeling, and preferably, integrated energy system modeling. Moreover, the hourly temporal resolution of the power sector should be maintained. Table 3 summarizes key modeling capabilities and concerning energy sectors and carriers for each P2X technology option.

[2] Providing consumers with time-varying electricity rates

[3] Payment to consumers to reduce their load at certain times

VRE curtailment and Conventional generation

VRE curtailment and conventional generation options have been used as FOs in the power sector. Modeling these options is relatively straightforward, as they do not involve other sectors or energy carriers. Still, the hourly temporal resolution remains the key modeling capability for these options. From the energy security perspective, modeling conventional generation may require modeling capacity mechanisms[4], preferably in combination with cross border power trade.

Cross border trade

The EU is promoting an internal single electricity market by removing obstacles and trade barriers (see e.g. COM/2016/0864 final - 2016/0380). “The objective is to ensure a functioning market with fair market access and a high level of consumer protection, as well as adequate levels of interconnection and generation capacity”. One of the products of an internal EU electricity market is the potential for offering flexibility in the power system, as the load can be distributed among a larger group of producers and consumers. For the Dutch context, Sijm et al. identified the cross border power trade as the largest flexibility potential for the Netherlands. Similar to other flexibility options, one of the key modeling capabilities here is the hourly temporal resolution.

Flexibility Options		Key modeling capability
Storage	Daily (e.g. solid state and flow batteries)	HTR
	Seasonal (e.g. pumped-hydro, TES, CAES)	ChO, HTR, P2Heat,
DR	Built environment	HTR, P2Heat, TAB, SC
	Transport	HTR, P2M, V2G
	Industry	HTR, P2G, P2H_2, P2L
	Agriculture	HTR, P2Heat, P2L
VRE curtailment and Conventional generation		HTR
Cross border power trade		EEM, HTR

Table 3, Key modeling capabilities for analyzing flexibility options

Abbreviations:
HTR= Hourly Temporal Resolution, ChO= Chronological Order, TAB= Thermally Activated Buildings, SC= Smart Controllers, P2M= Power-to-Mobility, V2G= Vehicle to Grid, P2G= Power-to-Gas, P2H_2= Power-to-Hydrogen, P2L= Power-to-Liquids, EEM= European Electricity Market

[4] Measures to ensure the desired level of security of supply in short-term and long-term.

Table 3 summarizes the required key modeling capabilities for representing and analyzing flexibility options in ESMs. The main requirement is the inclusion of (at least) an hourly temporal resolution. Models' capabilities can improve substantially by adding seasonal storage options, which require the inclusion of chronological order and different energy carriers. Moreover, the inclusion of cross border trade can play an important role in the optimal portfolio of flexibility options, especially in EU countries.

Uncertainty

Higher shares of intermittent renewables affect the reliability of power generation and distribution as residual loads become less predictable. For instance, the prediction accuracy of a single wind turbine generation decreases from 5-7% to 20% mean absolute error for the hour ahead and day ahead forecasts respectively [59]. The increased uncertainty of the power generation due to higher shares of VRE sources requires models to include short-term weather forecast and balancing mechanism in their calculations.

Uncertainty analysis gets more importance for long-term ESMs as they model the energy system for several decades in an uncertain future that can get affected by parameters outside the energy system boundaries. Energy system optimization models use four main uncertainty analysis methods, which are Monte Carlo Simulation (MCS), Stochastic Programming (SP), Robust Optimization (RO), and Modeling to Generate Alternatives (MGA) [60].

2.3.2. **Further electrification**

In 2017 almost 22% of EU final energy demand is satisfied by electricity, while heat consumption and transport account for the rest. Current heating and cooling production in the EU is mainly coming from fossil fuel sources, as renewable energy sources have a 19.5% share of gross heating and cooling consumption. The transport sector is highly dependent on fossil fuels with only 7.5% of final energy consumption from renewables. Therefore, decarbonization of the heat and transport sectors is getting more attention as it has a higher GHG emissions reduction potential. Further electrification of heating, cooling and transport sectors may contribute to GHG reduction, assuming the electricity is generated from renewables rather than fossil fuels. The EU commission suggests electricity as an alternative fuel for urban and suburban driving in its report entitled Clean Power for Transport.

Due to the high seasonal variation of heating and cooling demand profiles (mainly in the built environment), further electrification of this sector requires huge seasonal storage capacities or other flexible supply options. Currently, there are four main high capacity seasonal storage options, which are Pumped Hydro Energy Storage (PHES), Compressed Air Energy Storage (CAES), Thermal Energy Storage (TES), and Hydrogen Energy Storage

(HES). By using TES technologies, hourly heat and power demand profiles can be decoupled resulting in a higher potential for DR flexibility option [61]. TES technologies can be divided into three main groups based on their thermodynamic method of storing heat energy, which are sensible, latent, and chemical heat [62]. Sensible Heat Storage (SHS) technologies stock the heat by the difference in the materials' temperature, for example by warming up water or molten salt tank. Latent Heat Storage (LHS) technologies make use of Phase-Change Materials (PCM) in a constant-temperature process to absorb or release thermal energy. Chemical Heat Storage (CHS) technologies make use of Thermo-Chemical Materials (TCM) in a reversible endothermic or exothermic (i.e. a chemical reaction in which the heat is absorbed or released, respectively) thermochemical process, for example, the reversible Ammonia dissociation process (i.e. $2NH_3=N_2+3H_2$). Xu et. al. [63] provides an extensive review of current seasonal thermal energy storage technology options.

Further electrification of the energy system, which is expected to account for 36-39% of final EU energy consumption by 2050 [64], generates higher interdependencies between energy sectors. Single sector models, which are not able to capture sector coupling effects may provide misleading conclusions by neglecting these interdependencies. As more sources of intermittent renewables are deployed in the energy system, the further electrification implies further volatility of the energy system that highlights the higher demand for flexibility options. Moreover, analyzing sector coupling technologies such as EVs (P2Mobility), heat pumps and electric boilers (P2Heat), and electrolyzers (P2Gas) become more important. Inclusion of sector coupling options in the ESM requires modeling of electricity, transport, and heat sectors simultaneously. Due to high variations in the electricity supply, a fine temporal resolution should also be employed in transport and heat sectors in order to adequately address the flexibility issues of sector coupling.

2.3.3. **New technologies, technological learning, and efficiency**

Development of new technologies and technological change are key drivers of the transition to the low-carbon energy system and at the core of most energy-climate policies worldwide [65]. For instance, the price decline of PV cells from 3.37 USD/W to 0.48 USD/W in the last 10 years has made solar energy an economic option independent of subsidies.

New technologies

Development of new technologies makes available additional renewable energy supply sources such as advanced biofuels, blue hydrogen, deep geothermal, wave, and seaweed.

It also provides innovative opportunities for further integration of the energy system by implementing P2X technologies, which mainly consist of P2Heat, P2G, P2H_2, P2L[5], and P2Mobility technology options. The variable seasonal trend of renewable sources such as wind and solar increases the need for seasonal storage options such as thermal energy storage and CAES. CCS and CCU technologies can be considered as alternative solutions for conventional GHG emission emitters. Deep decarbonization of the industrial sector can be achieved by the development of new industrial processes while considering the whole value chain [66]. The development of zero energy buildings [67] and formation of energy neutral neighborhoods [68] can contribute to substantial energy savings in the built environment.

Technological learning

ESMs currently represent technological learning either exogenously or endogenously [69]. Technological change is prevalently expressed in a log-linear equation relating technology cost to its cumulative production units. This one-factor equation provides the learning rate, which is the cost reduction that is resulting from a doubling of the cumulative produced units of the concerned technology [70]. The prominent alternative is the two-factor equation that incorporates both cumulative produced units and R&D investments [71]. Endogenous Technological Learning (ETL) is widely used in long-term ESM analysis (e.g. see [72], [73]). ETL can be further elaborated as Multi-Cluster Learning (MCL) and Multi-Regional Learning (MRL). MCL (or so-called Compound Learning) describes a cluster of technologies, which share the same component and learn together. MRL differentiates between region-specific technological learning and global technological learning. The consideration of new technologies and technological learning can greatly affect the energy system modeling results, particularly in long-term models. For instance, Heuberger et. al. [74] conclude that the presence of global ETL results in 50% more economically optimal offshore wind capacity by 2050.

Energy efficiency

As part of the Clean Energy for all Europeans package, the EU sets binding targets of at least 32.5% energy efficiency improvement by 2030, relative to the business as usual scenario. This policy emphasizes particularly the built environment as the largest energy consumer in Europe. Although energy-efficient technologies provide financial and environmental costs reduction, they are not widely adopted by energy consumers. This "energy efficiency gap" can be a consequence of market failures, consumer behavior, and modeling and measurement errors [75]. Energy efficiency policies may induce the Rebound effect (or backfire), in which energy efficiency improvements lead to an increase

[5] Ammonia, Methanol, and other synthetic fuels (petrol, diesel, kerosene, etc.)

in energy use. The rebound effect may have a direct decreasing impact in energy consumption (e.g. a decrease in residential energy consumption), while having an indirect increasing impact (e.g. an increase in energy use by expansion of energy-intensive industries). Providing an estimate of the rebound effect magnitude can be challenging, while the existence and magnitude of this effect is a matter of discussion in the literature. Although energy-efficient technologies can play an effective role in energy system transition, modeling and analyzing its direct and indirect effects are challenging.

2.3.4. **Energy infrastructure**

Energy infrastructure has a key role in the low-carbon energy system transition by facilitating sectoral coupling, integrating renewable energies, improving efficiency, and enabling demand-side management. However, analyzing energy infrastructure can come up with some challenges, such as the complexities of distributing costs and benefits of investments and allocation of risk between investors and consumers. Conventional energy infrastructure facilities are usually managed by a monopoly as public goods that are not traded in a market. Therefore, it is challenging to clearly disaggregate costs and benefits of infrastructure changes due to energy transition. Long-term investment character of infrastructure and risk profiles of investors and consumers can be highly diverse as energy infrastructures can undergo drastic changes. Moreover, social acceptance of energy infrastructure plays a key role in energy transition, particularly in decentralized infrastructures such as CCUS networks, transmission lines, district heating, and local energy storage. Modeling the social acceptance of energy infrastructure requires a combination of qualitative and quantitative datasets which can be highly locally dependent.

Assuming the above-mentioned datasets are available, ESMs require specific capabilities to analyze energy infrastructure. The ESM should be geographically resolved, as energy infrastructure can have both local and national scales. Moreover, there is a need for GIS-based geographical resolution of ESMs as costs and benefits of energy infrastructures can change drastically by their geographical location.

2.3.5. **Decentralization**

Over the past decades, energy used to be supplied by large power plants and then being transmitted across the consumers. By emerging renewable energy supplies, a new alternative concept of the energy system is being developed. The decentralized energy system, as the name suggests, is comprised of a large number of small scale energy suppliers and consumers. A transition from a centralized fossil-fuel and nuclear-based energy system to a decentralized energy system based on intermittent renewable energy sources can be a cost-effective solution for Europe . The local energy supply reduces transmission costs, transmission risks, environmental emissions and to some extent promotes energy security, sustainable society, and a competitive energy market. On the other hand, it can increase costs in generation capacity investment, distribution, and energy reliability. Therefore, there is a need to determine the optimal role of energy system decentralization by carefully analyzing costs and opportunities.

Conventional energy modeling tools were based on the centralized energy system and they face difficulties answering the decentralized energy system demands. In the conventional energy models, the location of the power plants does not play an important role, while spatial detail may be critically important for renewables. For instance, economic potentials, solar potentials, generation costs, environmental and social impacts, network constraints, and energy storage potentials are some location-dependent factors that can vary greatly across different regions. Some other factors such as wind potential and infrastructural costs can vary greatly even with little dislocation. Therefore, a fine spatial resolution is required in order to assess the role of location-dependent parameters in the energy system.

National ESMs can use national, regional, or GIS (Geographical Information System) based spatial resolution. Using a fine spatial resolution can be limited by the available computational power and spatial data. Therefore, the choice of spatial resolution is the compromise between these two parameters. Due to the huge computational load of GIS-based ESMs, they are usually applied at urban level rather than national level. GIS-based models can be used in a data preprocessing phase in order to provide spatially resolved data sets for national ESMs. For instance, the global onshore wind energy potential dataset is produced at approximately 1 km resolution [76]. Assuming the availability of the spatial data, the computational limitation can be addressed by linking a coarse resolution energy model with a spatial modeling tool such as ArcGIS (e.g. see [77]).

2.3.6. **Human behavior**

Conventional energy models neglected social stakeholders as the energy system was managed and controlled by central decision-makers. In order to reach a sustainable low-carbon energy system, technical and social insights should get integrated in these models. According to the technology review of the U.S. Department of Energy, the balance of energy supply and demand is affected as much by individual choices, preferences, and behavior as by technical performance [78]. The reliability of energy models is often low because they are excessively sensitive to cost analysis while ignoring major energy policy drivers such as social equity, politics, and human behavior. Several recent studies indicated the role of social sciences in energy research. Social parameters are usually difficult to quantify, and consequently, are usually neglected in quantitative energy models. However, there are practical methods of integrating human aspects into technical energy models, such as the inclusion of prosumers and agent-based modeling.

Originally coined by Alvin Toffler in his 1980 book *The Third Wave* [79], *Prosumer* is the mixture of the words producer and consumer, explaining the active role of energy consumers in the production process. The conventional energy grid was dependent on the interaction between supplier and distributor, while in the decentralized energy system consumers play an active role. An important element of this new system is the role of prosumers i.e. consumers who also produce and share surplus energy generated by renewable energy sources with the grid and/or other consumers in the community. By emerging renewable energies at the microscale, prosumers are not only an important stakeholder of the future smart grids but also may have a vital role in peak demand management. However, social acceptance of the decentralized energy system faces several drivers and barriers that need quantification in order to be imported into energy models. The emergence of prosumers has increased the diffusion of social sciences in energy system modeling. In order to grasp an adequate knowledge of the decentralized energy system, the human behavior of the prosumers on energy grid should be considered alongside the techno-economical characteristics.

Based on the position of the decision maker, ESMs can be divided into two main categories. The common approach is the assumption of a system planner who optimizes the single objective function (e.g. system cost minimization). Contrary, agent-based models practice decentralized decision making by assuming autonomous agents who make a decision based on their own objective function that may be different from others. Agent-based modeling has been proposed by researchers as a suitable modeling approach for complex socio-technical problems and it is used in modeling the wholesale electricity markets considering human complexities. Ringler et al. provided a review of agent-based models considering demand response, distributed generation, and other smart grids paradigms. The term “Agent” can be used to describe different types of players in the energy system such as prosumers, power generators, storage operators, or policy makers. Agents optimize their own objective function, which can be based on economic (e.g. capital, NPV, and tariffs), technical (efficiency, emissions, and maximum capacity), and social (e.g. bounded rationality, neighborhood effect, and heterogeneity) factors. Including techno-economic factors in the objective function is relatively easier due to the quantitative nature of these parameters, while integrating qualitative social parameters remains a complicated task. Qualitative parameters such as the perceived weight of environmental costs and impacts, expected utilities, social networks, and communication can be estimated by socio-demographic factors and behavior curves.

2.3.7. **Capturing economic interactions**

Macroeconomic models follow a top-down analytical approach compared to techno-economic ESMs that use a Bottom-up approach. The analytical approach is the way to break a system down into elementary elements in order to understand the type of interactions that exist between them. This system reduction may be done in different ways. Based on the reduction approach, ESMs are usually differentiated into three main groups which are Top-down, Bottom-up, and Hybrid models.

Top-down (TD) models describe the energy-economy system as a whole and try to assess the energy and/or climate change policies in monetary units. These models mainly describe the relations between the energy system and the variations in macroeconomic and environmental factors such as economic growth, demographics, employment rate, global warming, and GHG emissions. Consequently, top-down models lack detail on current and future technological options which may be relevant for an appropriate assessment of energy policy proposals. Macroeconomic equilibrium models are an example of top-down models.

Bottom-up (BU) models, provide a higher degree of technological detail (in comparison to top-down models). Characterized by a rich description of the current and prospective energy supply and end-use technologies, bottom-up models picture energy systems evolutions as resulting from a myriad of decisions on technology adoption. They can compute the least-cost solution of meeting energy balances subject to various systems constraints, such as exogenous emission reduction targets.

Hybrid models (i.e. linking TD and BU models) can be a solution to have a top-down consistency while maintaining bottom-up detail. The major advantage of top-down models is their consistency with welfare, market, economic growth, and other macroeconomic indicators that leads to a comprehensive understanding of energy policy impacts on the economy of a nation or a region. On the other hand, they lack an appropriate indication of technological progress, energy efficiency developments, non-economical boundaries of the system, and other technical detail. Instead, bottom-up models describe the energy system with detailed technological properties. Moreover, bottom-up models lack feedback from the macro-effects of the technical changes in the overall economy. Therefore, closing the gap between top-down and bottom-up energy models results in more consistent modeling outcomes.

Model linking is not an exclusive solution for TD and BU models. Hourcade et al. [80] argued that the three main dimensions of an energy-economy system are: technological explicitness, microeconomic realism, and macroeconomic completeness. The main advantage of model linking is the ability to provide consistent results while considering the three dimensions of energy-economy systems. Model linking (i.e. modeling suite) can include only two dimensions or all the three dimensions. Each of these dimensions can be modeled with a number of different models depending on the complexity of the problem.

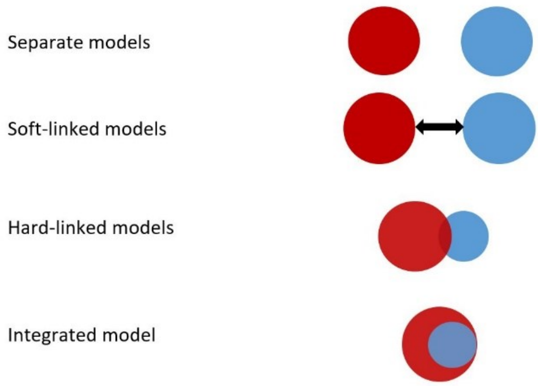

Figure 9, Model linking based on the linking degree

Source: [81]

The model linking approach can be classified into three subcategories, based on the level of linking. First, individual stand-alone models are linked together manually meaning that the processing and transferring of the information between models are controlled by the user, preferably in an iterative manner (i.e. soft-linking). Second, a reduced version of one model exchanges data with the master model while both running at the same time (i.e. hard-linking). Third, a combined methodology features in an integrated model through a unified mathematical approach (e.g. mixed complementarity problems [82]). Similarly, Helgesen [81] used another classification based on the linking type of models and the terminology proposed by Wene (i.e. soft-linking and hard-linking) [83]. The advantages of soft-linking can be summarized as practicality, transparency, and learning, while the advantages of hard-linking are efficiency, scalability, and control.

2.3.8. **Summary**

The above discussion of the main challenges of the present and future ESMs identified several required modeling capabilities, which are summarized in Table 4.

In order to review models based on mentioned challenges, required capabilities are grouped into several model assessment criteria in Table 5. It should be noted that the integrated energy system analysis capability is not mentioned further as all reviewed models are integrated. Moreover, the linking ESMs with TD models capability will be discussed further in Section 2.5.

<table>
<tr><th>Challenges</th><th>Required modeling capabilities</th></tr>
<tr><td rowspan="2">Intermittency and flexibility</td><td>Flexibility options (Storage, DSM, VRE Curtailment, Conventional generation, Cross border trade)</td></tr>
<tr><td>Fine temporal resolution (HTR, HTR time-slices + ChO, HTR time-slices)</td></tr>
<tr><td rowspan="3">Further electrification</td><td>Integrated energy system analysis</td></tr>
<tr><td>Sectoral coupling technologies (P2Mobility, P2Heat, P2Gas)</td></tr>
<tr><td>Seasonal Storage (PHES, CAES, TES, LHES)</td></tr>
<tr><td rowspan="2">New technologies and technological change</td><td>The granularity of presented technologies (current basket of technologies, P2X family, new renewable sources, and storage options)</td></tr>
<tr><td>Technological learning (exogenous, 1-factor ETL, multi-factor ETL, MCL, MRL)</td></tr>
<tr><td>Decentralization</td><td>Fine spatial resolution (national, regional, GIS)</td></tr>
<tr><td>Human behavior</td><td>Socio-economic parameters (demand profile, learning, risk profile, communication with others, perceived environmental value, and perceived discount factor)</td></tr>
<tr><td>Macroeconomic interactions</td><td>Linking ESMs with TD models (soft-link, hard-link, integrate)</td></tr>
</table>

Table 4, Summary of integrated energy modeling challenges and required modeling capabilities

Apart from the criteria that result from emergent challenges of future ESMs, three additional criteria are considered in Table 5, which are (i) the underlying methodology of the model in order to separate calculator models from non-calculator ones, (ii) the source of the model's datasets in order to measure input-data quality, and (iii) the accessibility and the number of the model's applications in order to determine the models' use and acceptance in the literature.

<table>
<tr><th>Capabilities</th><th>Criteria</th></tr>
<tr><td>Flexibility options (Storage, DSM, Curtailment, Conventional generation, Cross border trade)
Seasonal Storage (PHES, CAES, TES, HES)
Sectoral coupling technologies (P2Mobility, P2Heat, P2Gas)
The granularity of presented technologies (current basket of technologies, P2X family, new renewable sources, and storage options)
Technological learning (exogenous, 1-factor ETL, multi-factor ETL, MCL, MRL)</td><td>Technological detail and learning</td></tr>
<tr><td>Fine temporal resolution (HTR, HTR time-slices + CO, HTR time-slices)</td><td>Temporal resolution</td></tr>
<tr><td>Fine spatial resolution (national, regional, GIS)</td><td>Spatial resolution</td></tr>
<tr><td>Human behavior (agent type, neighborhood effect, and heterogeneity)</td><td>Social parameters</td></tr>
<tr><td rowspan="3">General capabilities</td><td>Modeling methodology</td></tr>
<tr><td>Data use</td></tr>
<tr><td>Accessibility and Application</td></tr>
</table>

Table 5, The list of assessment criteria based on modeling capabilities and our suggestions

2.4. The Multi-Criteria Analysis

Considering the criteria regarding the future low-carbon energy systems and available models it can be concluded that no perfect model exists. However, models can be assessed based on the list of criteria such as temporal resolution, spatial resolution, the social aspect, data source quality, accessibility, and application of the model that are summarized in Table 5 of Section 3.7.

The capability of the model in each criterion is given a score from five (highest) to one (lowest) as presented in Table 6. The importance of each criterion is indicated in Table 8 as the weight of each criterion. The results are highly dependent on the scores and weights, which are both - to some extent - subjective. Readers can alter the results by incorporating new criteria or changing the perspective weights. In the following, these modeling capabilities and the corresponding scores are explained.

Technological detail and learning

There are two parameters that differ across integrated ESMs, which are the inclusion of flexibility options and the inclusion of technological learning. Therefore, models can be grouped into three groups: (i) no flexibility option and no technological learning with score one, (ii) the inclusion of either flexibility options or technological learning with score three, (iii) the inclusion of flexibility options and technological learning with score five.

Temporal resolution

ESMs usually balance the supply and demand on a yearly basis or a limited amount of (hourly) time-slices per year. Nevertheless, some models have a higher temporal resolution and balance the system on an hourly basis. Reviewed models can be categorized in three groups: (i) temporal resolution on yearly basis with score one, (ii) time-slice approach with score three, (iii) hourly temporal resolution with score five.

Spatial resolution

Some models have the capability to model the regions inside a country. This ability can provide regional insights on energy system policies and vice versa. Although the limited computational capacity and the lack of data make it difficult to perform a detailed regional analysis, some models balance the system in different regions inside the country based on different capacities and properties of regions (e.g. ESME in the UK). Reviewed models are divided in three groups: (i) models without regional depth with score one, (ii) models which consider regions with score four, since it is a considerable improvement, (iii) models which consider GIS data with score five.

Social parameters

The role of social analysis in techno-economic models is usually negligible. However, some modeling tools practice multi-agent programming in order to model qualitative aspects of energy system stakeholders decision making. Models are categorized in two groups: (i) models which capture socio-economic parameters only based on demand curves with score one, (ii) agent-based models which consider a set of decision-making rules for different stakeholders in the energy system with score five.

Modeling methodology

Reviewed models practice a different set of methodologies. In this review, the main categorization between methodologies can be made between the calculator and non-calculator methodologies. Therefore, models can be grouped into two groups: (i) calculator models with score one (ii) non-calculator models with score five.

Data use

The depth of technical detail and the quality of data play a crucial role in providing accurate insights into the energy system with regard to new technologies and sectoral coupling. Moreover, data access is the first limitation of energy system research as databases are rather private. Models can be divided into five groups: (i) models which do not indicate their data source with score one, (ii) models which use generalized open-source data with score two, (iii) models which use limited country-specific data with score three, (iv) models which use detailed open-source data with score four, (v) models which use detailed country-specific datasets possibly in combination with global datasets with score five.

Accessibility

Open-access models provide an opportunity for other modelers and experts to test the model and add their insights. With this regard, models are divided into five groups: (i) models which provide no access with score one, (ii) models which provide limited access with score two, (iii) models which are commercial with score three, (iv) models which are open-source but need permission with score four, (v) models which are completely open-source and accessible through web with score five.

Application

A model with more applications and users is known among experts and it makes it easier to disseminate and discuss results with other researchers. Models are grouped in five sets: (i) models which have no publication yet score one, (ii) models which have been applied in one country with score two, (iii) models which have been applied in two countries with score three, (iv) models which have been applied across EU countries with score four, (v) models which have been applied in many countries and are well-known with score five.

Criteria	*Score*				
	1	2	3	4	5
Technological detail and learning	No flexibility option and No technological learning		Flexibility options or technological learning		Flexibility options and technological learning
Temporal resolution	More than a year		Hourly time-slices		Hourly temporal resolution
Spatial resolution	Without regional depth			Considering regions	Considering GIS data
Social parameters	Demand curves				ABMs
Modeling methodology	Calculator				Non-calculator
Data source	No data	Generalized open-source global data	Limited country-specific data	Detailed open-source global data	Detailed country-specific datasets possibly in combination with global datasets
Accessibility	No access	Limited access	Commercial	Open-source upon request	Open-source and accessible through web
Application	No publication	Applied in one country	Applied in two countries	Applied across EU countries	Applied globally

Table 6, Summary of the corresponding scores to modeling capabilities in each criteria

Table 7 demonstrates the MCA analysis table with equal weight for all criteria. Right to the score of each model for each criterion, the weighted percentage of that criteria in the model's total score is demonstrated. This percentage is calculated endogenously, as explained by Equation 1. It indicates the share of the models' score in each criterion out of the models' total score.

$$Weighted\ percentage_{(Model,Criterion)} = \frac{Score_{(Model,Criterion)} \times Weight_{(Model,Criterion)}}{\sum_{c=1}^{c=8}\left(Score_{(Model,c)} \times Weight_{(Model,c)}\right)}$$

Equation 1, The formula for calculating the weighted percentage of each (Model, Criterion)

Model name	Modeling methodology		Technological detail		Temporal resolution		Spatial resolution		Social parameters		Data source		Accessibility		Application		Total
PRIMES	5	15%	5	15%	3	9%	4	12%	5	15%	4	12%	3	9%	4	12%	4.13
REMix	5	15%	5	15%	3	9%	5	15%	1	3%	5	15%	4	12%	5	15%	4.13
MARKAL f.	5	16%	5	16%	3	9%	4	13%	1	3%	4	13%	5	16%	5	16%	4.00
METIS	5	16%	3	10%	5	16%	5	16%	1	3%	4	13%	4	13%	4	13%	3.88
ENSYSI	5	17%	3	10%	5	17%	1	3%	5	17%	5	17%	4	14%	1	3%	3.63
OSeMOSYS	5	18%	5	18%	3	11%	4	14%	1	4%	2	7%	5	18%	3	11%	3.50
OPERA	5	19%	5	19%	3	12%	1	4%	1	4%	5	19%	4	15%	2	8%	3.25
NEMS	5	19%	5	19%	1	4%	4	15%	1	4%	4	15%	4	15%	2	8%	3.25
POLES	5	19%	5	19%	1	4%	4	15%	1	4%	4	15%	2	8%	4	15%	3.25
SimREN	5	19%	3	12%	5	19%	4	15%	1	4%	5	19%	1	4%	2	8%	3.25
EnergyPLAN	1	4%	3	12%	5	20%	1	4%	1	4%	5	20%	5	20%	4	16%	3.13
ESME	5	21%	3	13%	3	13%	4	17%	1	4%	5	21%	1	4%	2	8%	3.00
IWES	5	21%	3	13%	5	21%	4	17%	1	4%	3	13%	1	4%	2	8%	3.00
STREAM	1	4%	3	13%	5	22%	4	17%	1	4%	2	9%	5	22%	2	9%	2.88
ETM	1	5%	3	16%	5	26%	1	5%	1	5%	2	11%	4	21%	2	11%	2.38
LEAP	1	5%	1	5%	1	5%	4	21%	1	5%	4	21%	3	16%	4	21%	2.38
E4Cast	5	28%	1	6%	1	6%	4	22%	1	6%	3	17%	1	6%	2	11%	2.25
DynEMo	1	6%	3	18%	5	29%	1	6%	1	6%	1	6%	2	12%	3	18%	2.13
IKARUS	5	29%	1	6%	1	6%	1	6%	1	6%	5	29%	1	6%	2	12%	2.13
Weights	1		1		1		1		1		1		1		1		8

Table 7, The MCA analysis table with equal weights

PRIMES gets a high score mainly due to the inclusion of social parameters, while the high score of REMix is due to its high spatial resolution. These models merely demonstrate improved capabilities compared to others; therefore, it does not mean that these models are "best" models. Moreover, some features of models are not reflected in this table. For instance, METIS works complementary to long-term ESMs as it only simulates a specific year. Besides, the MCA results can be changed considerably by assigning slightly different scores to various criteria as total scores are relatively close. Models such as the MARKAL family and METIS demonstrate high scores mainly due to their high granularity; however, they lack the inclusion of social parameters. ENSYSI includes social parameters while lacking spatial resolution and application.

Sensitivity analysis

Addressing all the policy-induced challenges of the energy system requires a comprehensive ESM that is not available currently. Therefore, a compromise should be made based on the challenges that the model is designed to address. Based on this compromise, a weighted decision matrix can be formed. Here the challenges are divided into two main groups, which are first: intermittency, flexibility, and further electrification; and second: human behavior and decentralization. The first group of challenges puts emphasis on technological detail, high temporal and spatial resolution; while the second group of challenges emphasizes on inclusion of social parameters and high spatial resolution. Table 8 summarizes an example list of challenges and corresponding weights. The importance of each criterion in addressing challenges is weighted from five (highest) to one (lowest). It should be noted that these weights are entirely subjective, thus, the reader can make his own decision tables based on different weights.

Challenges	Modeling methodology	Technological detail	Temporal resolution	Spatial resolution	Social parameters	Data source	Accessibility	Application
Intermittency, flexibility, and further electrification	3	5	5	5	1	3	1	1
Human behavior and decentralization	3	3	3	5	5	3	1	1

Table 8, The weight table of two groups of challenges for the MCA

Using Table 8 for updating the MCA analysis table will lead to a slightly different result which is presented in Table 9. For the first group, it is expected that models with high scores in technological detail, temporal resolution, and spatial resolution will get higher total scores. The REMix model gets a high total score mainly due to the inclusion of high spatial resolution with the use of GIS data and the inclusion of key flexibility and storage technologies with the exogenous technological learning. The METIS model provides lower technological detail by neglecting technological learning while incorporating hourly temporal resolution and GIS-based spatial resolution. For the second group, the inclusion of social parameters and fine spatial resolution gains importance. Models with the inclusion of social parameters such as PRIMES and ENSYSI get higher scores. Although the METIS model does not include social parameters, it keeps a high score due to its fine spatial resolution.

Equal weights	First group perspective	Second group perspective
REMix	REMix	PRIMES
PRIMES	METIS	REMix
MARKAL f.	PRIMES	METIS
METIS	MARKAL f.	ENSYSI
ENSYSI	SimREN	MARKAL f.
OSeMOSYS	OSeMOSYS	SimREN
SimREN	IWES	OSeMOSYS
NEMS	ENSYSI	IWES
POLES	NEMS	NEMS
OPERA	POLES	POLES
EnergyPLAN	ESME	ESME
IWES	OPERA	OPERA
ESME	STREAM	STREAM
STREAM	EnergyPLAN	EnergyPLAN
ETM	ETM	E4Cast
LEAP	E4Cast	LEAP
E4Cast	DynEMo	ETM
DynEMo	LEAP	IKARUS
IKARUS	IKARUS	DynEMo

Table 9, Changes in the MCA analysis table based on perspective weights

Irrespective of perspective weights, four models stay at the top of the MCA table which are REMix, PRIMES, METIS, and the MARKAL family models. These models demonstrate high scores in nearly all criteria, while a low score in one criterion (for instance, lack of social parameters in REMix) is compensated with a high score in another criteria (in this case, high temporal and spatial resolution). These four models are developed recently (e.g. REMix and METIS) or they are under constant development (e.g. MARKAL family and PRIMES). It shows the trend of integrated energy system modeling points towards the models with improved capabilities in all criteria.

Other models stay at the nearly same ranking position except for IWES, ENSYSI, and EnergyPLAN, which change their position considerably (i.e. more than two steps change). This position change can be explained by the asymmetry in these models' scores in the MCA table. For instance, the IWES model gets a high score in the first four criteria while getting a low score in the last four criteria.

The MCA represents an overview of the current state of ESMs with regard to low-carbon energy system modeling challenges. However, there is a need for adding new capabilities to current ESMs in order to answer future modeling challenges. In the next section, based on our observation from the current state, we discuss two potential modeling solutions to answer future energy system modeling challenges. These solutions are expanding single models and/or linking different models.

2.5. Developing and Linking models

It is not a practical conclusion to decide on the best model that addresses challenges regarding low-carbon energy systems, as each model has specific pros and cons. From a techno-economic point of view, the MCA indicates that for modeling the low-carbon energy system, current models require specific capabilities such as hourly temporal resolution, regional spatial resolution, inclusion of sectoral coupling technologies, technological learning, and inclusion of social parameters. There are major gaps between policy questions and modeling capabilities in the criteria which were used to assess the models' performance. However, these criteria mainly focus on the technical policy questions rather than the entire technical, microeconomic, and macroeconomic aspects. Although techno-economic models are rich in detail, they lack the capability to answer microeconomic and macroeconomic policy questions. Therefore, specific models, such as energy market models and general equilibrium models, have been developed. Due to the strong interconnection between energy and economy, mixed policy questions arise that require analyzing the technical, microeconomic, and macroeconomic aspects of the energy-economy system. Such analysis can be conducted either by developing single models or combining different models (i.e. soft-linking, hard-linking, or integrating).

2.5.1. **Developing single models**

Current single models can be developed and/or extended by incorporating further capabilities up to acceptable computational limits. Considering the limitations, the modeler makes choices and/or trade-offs on extensions to the model. Developing a single model that can cover all the mentioned gaps would face limitations, such as complicated mathematical methodology and limited computational capacities (except generic limitations such as high data needs and lack of transparency).

Some common energy system modeling methodologies are optimization, simulation, accounting, multi-agent, and equilibrium. Each mathematical methodology is developed to answer specific energy modeling questions. Integrating two different methodologies can be mathematically very complicated (e.g. Mixed Complementarity Problems in which the optimization and equilibrium formulations are mixed) or not feasible (e.g. mixing Optimization and Simulation formulations). Therefore, single ESMs are naturally limited by their underlying methodology.

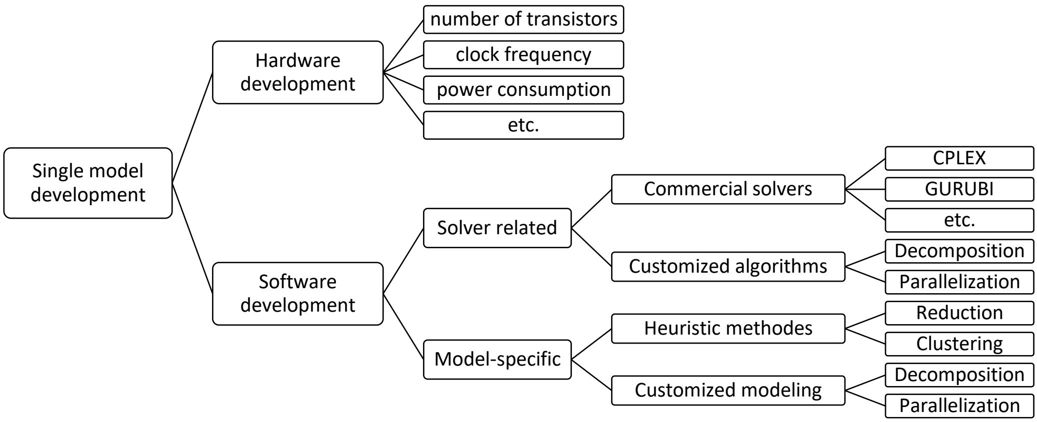

Figure 10, Single model development approaches

One of the main limitations for improving the temporal and geographical resolution of ESMs is the computational capacity. The computational limitation can be addressed either by hardware or software development. Hardware development follows an exponential growth and relates to improvements in the number of transistors, clock frequency, and power consumption of processors. Gils et al. divided software methods to improve computing times of linear optimization ESMs into solver-related and model-specific methods [84]. Solver-related methods focus on improving the solving methodology by using different off-the-shelf algorithms, such as LINDO, CPLEX, GURUBI, and MOSEK, or by practicing customized algorithms, such as Bender's decomposition[6] and parallelization[7]. Model-specific methods relate to heuristic methods, such as clustering, model reduction, decomposition, and parallelization.

Hardware-related developments proceed at a specific pace that usually is not affected by energy system modelers as users. Solver-related developments are followed by a few energy system modelers, while the rest of the energy system modeling community follows model reduction and clustering methods that can be applied on temporal resolution, spatial resolution, and technological detail. Depending on the research questions to be answered, energy system modelers reduce or coarsen the resolution of the model in order to provide an answer in an adequate timeframe. Therefore, the modeler should make a trade-off between different modeling capabilities by making smart assumptions.

2.5.2. **Linking models**

An alternative approach to overcome the limitations of single model development is to form a modeling suite by combining different models. Model linking can be done between any set of desired models in order to enhance modeling capabilities. However, two types of energy model linking are more frequent in the literature: (1) Linking BU and TD models such as optimization energy system models (OESMs) linked with CGE models, and (2) linking two BU models such as OESMs linked with energy market models (i.e. unit commitment or dispatch models). Although linking models provides further modeling capabilities, it comes with certain challenges such as identification of connection points in soft-linking, convergent solution in soft-linking, and mathematical formulation for integrated linking. Collins et al. have provided a comprehensive overview of different energy model linking practices and their advantages, limitations, and applicability [85]. In summary, linking models can be resource-intensive as it requires the knowledge of different modeling frameworks. Each model has its own set of assumptions and methodologies, which makes it complicated to maintain the harmonization of modeling assumptions in all steps of linking. The lack of harmonization in assumptions may result in inconsistent results from linked models. Although this process seems straightforward, it is rather a puzzling procedure as ESMs are moderately complex. Therefore, having an overview of different energy models and their capabilities is essential to provide the desired modeling suite.

A linking approach is proposed for addressing current energy system modeling gaps. Table 10 provides an overview of identified energy modeling gaps and corresponding linking

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[6] A method to decompose a very large Linear Program into smaller solvable LP and NLP [232].

[7] A method to divide a large program into smaller programs and solving all of them at the same time.

suggestions. These suggestions can form a modeling suite that involves four different models, namely, the Energy System Model (ESM), the Energy Market Model (EMM), the Macroeconomic Model (MEM), and the Socio-Spatial Model (SSM).

Current energy system modeling gaps	**Suggestions**
Lack of sectoral coupling technologies between electricity, heat, and transport sectors.	Developing a long-term planning optimization **Energy System Model (ESM)** that involves all energy sectors, hourly temporal resolution, regional spatial resolution, seasonal storage options, and technological learning
Lack of new seasonal storage technology options such as TES and HES.	
Lack of endogenous technological learning rates.	
Lack of hourly temporal resolution for capturing intermittent renewables and corresponding potentials.	
Lack of regional spatial resolution for analyzing energy flows between regions across a country.	Hard-linking ESM with a **Regional Energy System Model (RESM)** that involves resolved spatial resolution, land use analysis, and infrastructure analysis
Lack of fine geographical resolution options such as GIS, fine mesh, and clustering for analyzing decentralized intermittent supply and infrastructure costs and benefits	
Lack of spatially resolved datasets such as infrastructure and local storage.	
Simplistic modeling of human behavior in the current ABMs.	Developing an ABM simulation **Socio-Technical Energy Model (STESM)** that involves stakeholders' behavior, local and neighborhood effects, bounded rationality, and perceived environmental values.
The focus of current datasets is only on technological detail, rather than stakeholders' behavior.	
High dependence of ESMs on consumer load profiles.	
Lack of national energy modeling consistency with a European (or an international) energy market.	Hard-linking ESM with an international (or European) **Energy Market Model (EMM)** that involves an optimal dispatch electricity market, the gas and oil market, hourly temporal resolution, regional spatial resolution, and a detailed generation database
Lack of energy modeling consistency with macroeconomic indicators	Soft-linking ESM with a **Macroeconomic Model (MEM)** such as a Computable General Equilibrium (CGE) model that involves the whole economy

Table 10, Model development and model linking suggestions based on the identified energy modeling gaps

The suggestions in Table 10 can be framed in two separate modeling suites based on the methodology of the core ESM. The first modeling suite can be formed around an Optimization ESM (OESM) that provides the cost-optimal state of the energy system assuming a fully rational central social welfare planner. The second modeling suite uses a Socio-Technical ESM (STESM) that demonstrates a more realistic state of the energy system by assuming profit maximizer agents who consider social decision-making parameters, such as behavioral economics, bounded rationality, neighborhood effect, and technology diffusion curve, in their decision-making process.

A: The core ESM

The core component of the suggested modeling suite is the presence of a central techno-economic ESM as an information processor hub that exchanges the outputs with different models. Based on the current state of the energy system and future scenarios, the ESM can determine the technology and energy mix, commodity and energy prices, amount and price of emissions, and total energy system cost. However, this standalone analysis is based on specific scenario assumptions such as demand profiles, energy import and export profiles, decentralized energy supply prospects, and macroeconomic expectations. It is suggested to use linear relations (i.e. linear optimization methodology) to keep the computational load manageable.

While the optimization framework determines the theoretically optimal state of the energy system, the simulation methodology can demonstrate feasible pathways to reach the optimal state. Therefore, by comparing the results of the optimization and simulation frameworks the gap between the optimal solution and the feasible solution (that is symbolically demonstrated in Figure 11) can be identified. Several policy parameters can affect the width of this gap by bringing the feasible solution close to the optimal one. Therefore, the analysis of the simulation and the optimization methodologies can elaborate on the role of each policy parameter on reaching to the optimal state of the energy system considering policy targets.

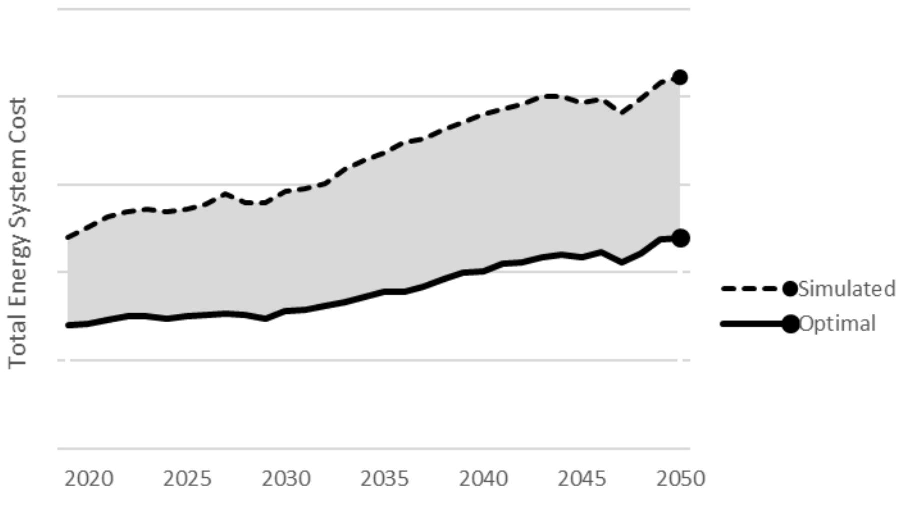

Figure 11, The symbolic gap between the results of the simulation and optimization methodologies.

Based on the review and the MCA, several optimization ESMs such as TIMES and REMix can be used as the core ESM of the modeling suite mainly due to their fine temporal resolution and ample technological detail. Agent-based simulation ESMs are not as common as optimization ESMs; therefore, only ENSYSI and PRIMES can be selected from the reviewed models as simulation core ESMs.

B: Hard-linking with the regional model

Current ESMs lack the capability to model the regional implications of the energy system such as decentralized supply and demand, infrastructure costs and benefits, land use, and resource allocation. Although some local energy system models such as EnerGis [86] and GISA SOL [87] provide geographically resolved energy system analysis, they lack the interaction with other regions of the country. As the regional variations of the energy system can have drastic effects on the energy system, it is suggested to hard-link the regional model into the core ESM. Improving the geographical resolution of ESMs can be done in different ways depending on research questions and available resources. For instance, after identifying spatially sensitive parameters of the energy system, such as heat supply location, renewable power production, transmission capacity expansion, and storage infrastructure, Sahoo et al. provide a framework to integrate them into an ESM (i.e. the OPERA model) [88]. Focusing on infrastructure, Van den Broek et al. cluster the CO_2 source regions using the ArcGIS software and then incorporate the spatially resolved data into the MARKAL-NL-UU as the optimization-based ESM [89].

C: Hard-linking with the energy market model

For well-connected countries, it is suggested to hard-link an EMM with the core ESM to capture the flexibility potential of the cross-border energy trade, albeit some studies use the soft-linking approach. In particular, for EU countries, this hard-linking is necessary as the interconnection Flexibility Option (FO) can be in direct competition with domestic FOs such as demand response or storage. EMMs usually use the MILP underlying methodology in order to model unit commitment; therefore, the inclusion of EMM inside ESM can be computationally intensive. It is suggested to use a linear optimization methodology in accordance with the core ESM to reduce computational load, while reaching to a “fair” estimate of the energy, particularly electricity, import and export flows.

Assuming the regional and interconnection capabilities are integrated into the core ESM, in order to capture consistent economic analysis, one soft-linking loop is suggested as follows.

D: Soft-linking with a macroeconomic model

This loop incorporates a macroeconomic model, which keeps demand and supply of commodities in equilibrium based on the statistical economic data such as the supply and demand of commodities, capital stocks and investments, demographics, labor market, and trade and taxes tables. The ESM outputs such as energy prices, energy mix, and emissions are fed into the MEM to update the supply and demand and price tables of energy and fuel commodities. The MEM provides the equilibrium demographics, GDP and income, monetary flows between economic sectors, trade, and employment rate. This loop can be performed one time or it can continue until the results reach a convergence criterion, which is a user-defined criterion that determines the maximum gap between results of two models.

Moreover, MEM outputs can feed into an ABM simulation ESM in which consumer demand profiles are generated based on demographics, income, and employment. The SESM analyzes the social aspects of the energy systems such as stakeholders' behavior, bounded rationality, imperfect communication, and environmental perceived value.

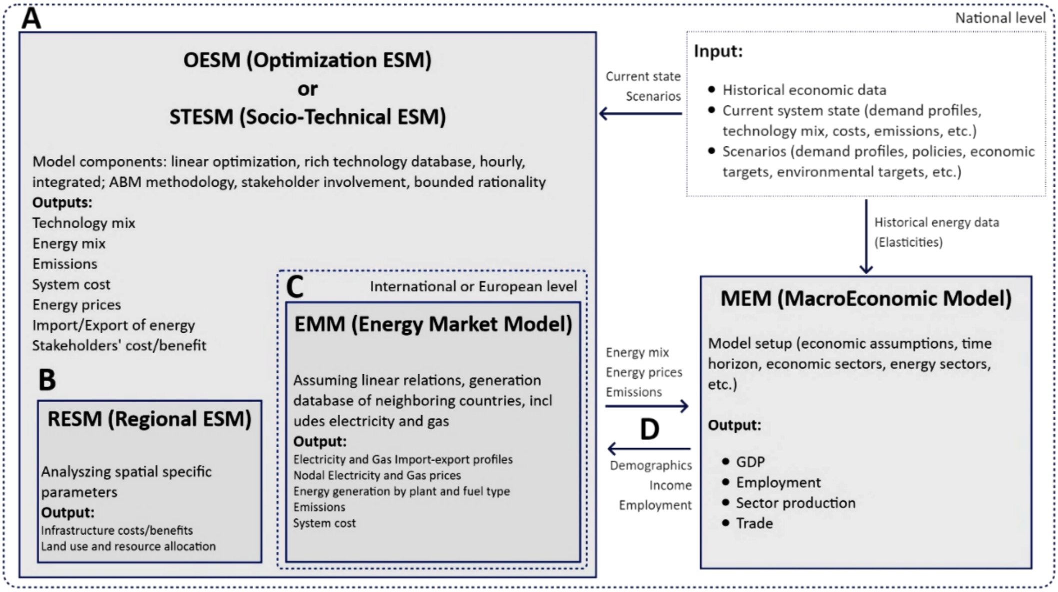

Figure 12, Optimization-based or Simulation-based conceptual model linking framework for the low-carbon energy system modeling suite

The choice of models, connection points, and scenarios, are dependent on the aims of the energy system modeling, available expertise and resources, and access to models and datasets.

A limitation of this study is that all the information about models has been gathered from officially published documents, which may get outdated quickly as the models are constantly under development. Therefore, this review provides rather a static view on ESMs. Only a limited number of energy system models were presented in this review, which is mainly due to limited time, resources, and access to modeling databases. There can be other challenges regarding the modeling of low-carbon energy systems that were not covered explicitly in this study. Some examples are the need for energy policy harmonization, energy market design, business models of new technologies, legislation and legal aspect of the energy transition, and social acceptance implications of the energy transition. Another limitation of this study is the use of multi-criteria analysis, in which scores are subjectively assigned, although a clear explanation is provided. Furthermore, the MCA only considered single ESMs while in practice a combination of models can be analyzed. A more comprehensive MCA would consider the capabilities and limitations of modeling suites.

Linear programing formulation of a high temporal and technological resolution integrated energy system model for the energy transition [8]

Abstract

Models with a wide technological representation of energy systems can hardly adopt hourly resolutions to study the energy transition towards low-carbon technologies due to extended problem size. This compromises the model's ability to address the challenges of variable renewable energy sources and the cost-effectiveness of cross-sectoral flexibility options. This methodology presents a linear program model formulation that simultaneously adopts different temporal representations for different parts of the problem to overcome this issue. For instance, all electricity activities and their infrastructure representation require hourly constraints to better replicate system feasibility. The operation of gaseous networks is settled out with daily constraints. The balancing of the other activities of the system is represented with yearly constraints. Furthermore, the methodology adopts an hourly formulation to represent in detail 6 cross-sectoral flexibility archetypes: heat and power cogeneration, demand shedding, demand response, storage, smart charging and electric vehicles. The model can successfully solve the transition problem from 2020 to 2050 in 5-year intervals with more than 700 technologies and 140 activities (including the electricity dispatch of the Netherlands and 20 European nodes) in less than 6 hours with a normal computer.

[8] This chapter is published in the MethodsX journal (https://doi.org/10.1016/j.mex.2022.101732)

3.1. Introduction

Energy system optimisation models (ESOMs) are a tool that allows us to identify ways of reaching decarbonisation targets in a cost-optimal way. To do so, they model the operation of the technologies present in all the system sectors using and producing energy and emitting CO_2 and the investments behind those technologies for the entire energy transition period. Due to this scope, IEM presents an extensive versatility and can be used for many different purposes, such as exploring technology configurations, providing policy advice, and analysing development paths. The suitability of ESOMs for different applications depends on the granularity and detailing of the model. For instance, a crucial topic for the energy transition is to analyse the role that variable renewable energy sources (VRESs) play in different sectors of the energy system. However, to adequately address the topic, it is necessary to correctly account, at different points of the transition, for the hourly operation of VRES and flexible sectoral technologies able to help with the challenges brought by VRES [90]. The latter presents a significant computational challenge due to the large problem size resulting from the high sectoral, technological, spatial, and temporal resolutions required, resulting in the need for modelling choices to address the issue. To understand this, different key modelling elements must be considered, notably the ones enlisted below:

- The whole transitional period from 2020 to 2050 with perfect foresight;
- Hourly sequential representation in the operation of technologies connected to the electricity network;
- All the sectors of the energy system modelled simultaneously, accounting for crucial feedback;
- Consideration of all of the GHG emission sources that are accounted for within reduction targets;
- A wide representation of the different technologies able to provide flexibility to the system, acknowledging their operational constraints;
- An adequate temporal resolution for technologies connected to gaseous networks (hydrogen and natural gas);
- A representation of the key infrastructure networks enabling the transport of energy carriers in the system.

ESOMs have been used extensively in the energy modelling community; however, they come with their own shortcomings, and a model that considers all the above elements simultaneously does not exist. The TIMES model [91], for example, provides a detailed techno-economic representation of all energy sectors, sector coupling technologies, and infrastructural limitations while using “integral”[9] time slices instead of hourly temporal resolution. TIMES can allow for hourly modelling instead of time slices, but due to the impracticality of the resulting problem size, it cannot be found in academic publications. Using aggregated time slices overestimates the potential contribution of large base-load power plants and underestimates the need for supply-demand management and storage with high shares of VRES [92]. Like TIMES, OPERA provides a detailed techno-economic representation of the energy system; however, it lacks the multiperiod optimisation methodology [93]. Neglecting the multiperiod optimisation undervalues the role of the current technological stock and its techno-economic lifetime on system costs. PyPSA provides an open-access energy system model that emphasises power network details such as the physics of power flow according to the impedances in the network [94] at the expense of a simpler technological representation of other sectors. Compared to other ESOMs, OseMOSYS requires less time commitment to operation, and being open-source, it requires no upfront financial investment; however, it lacks the inclusion of high technological details and infrastructure constraints [95]. REMix uses the EnDAT tool [39] to preprocess the heat and power demand data for incorporating geospatial variations in the hourly optimisation model [96]. However, the model’s main focus is the power system and does not provide a complete sectoral description of the energy system and its emissions. A model presented by Göke in 2021 addresses the energy transition while allowing for different spatial and temporal resolutions for different energy carriers [97], but it uses aggregated volumes to identify the energy carriers demand projections rather than base them on economic activities. Many other models also address the above elements but were omitted from this brief literature review to avoid redundancies. However, a complete literature review[10] was carried out before, in which an extensive list of models was explored [98]. None of the models identified addressed all the elements simultaneously.

To fill this knowledge gap and to be able to provide a complete and comprehensive approach to study low-carbon potential scenarios with high levels of VRES for the transition in the Netherlands, we developed an integrated energy system model named IESA-Opt. This model has already been used to explore the decarbonization transition in the Netherlands’ energy system [99], and to measure the results impact and computational weight of modelling capabilities [100]. IESA-Opt is an optimisation model using a linear programming (LP) formulation to determine the cost-optimal investment path in the transition towards 2050 decarbonisation targets and the operation of the

[9] Approximate the (residual) load duration curve by dividing a year into a limited number of time slices (typically 4-12) to represent seasonal, daily and diurnal variations in demand and supply. [304]

[10] That literature review is used as the pillar of the foundation of the model whose methodology is presented in this article, so it is recommended to revise it if further information is required.

technologies present in the system. An LP approach allows for representing the energy system with high sectoral, technological and temporal resolution while maintaining computational feasibility[11]. The chosen formulation also allows for the flexible framework used in the model, which enables the energy system to be described in clusters or to include geographical constraints of the model[12]. Conventional large-scale, long-term planning energy system models frequently use LP methodology to avoid excessive computational loads. Due to their narrower system scope, operational energy system models, especially power system models, employ a mixed-integer linear programming (MILP) methodology to account for binary or integer variables such as investment and unit-commitment decisions. The choice of LP over MILP methodology can considerably reduce the computational time without important deviations in the results, especially in energy systems with high shares of VRES [101]. The computational time of the LP formulation can be significantly lower than that of the MILP approach (up to 100 times) while providing relatively high precision in modelling relevant flexibility options [102]. The most significant modelling sacrifice of not using an MILP approach is that the concept of economies of scale cannot be represented through convex functions. However, the latter downside is counterweighted by the higher resolution of the activities considered by the model, which allows for different policy guiding approaches. Unfortunately, adequate testing of this hypothesis would require a contrasting MILP formulation that cannot be feasibly solved for such a large problem at reasonable times without the need for supercomputers.

3.2. IESA-Opt conceptual framework

To include all the activities of the energy system, the model differentiates between driver activities and energy activities. Being the driver activities those who create the need to use energy in the first place (e.g., the production of steel or the use of passenger cars), and the energy activities corresponding to specific forms of energy carriers (e.g., electricity or hydrogen). This means that the model needs to be fed (exogenously) with the projected production (or usage or demand) volumes of the driver activities, data often found in macroeconomic projections. However, it endogenously determines which technologies are used to meet such volumes accordingly with the 'menu' of technological options

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[11] A model run where all the model capabilities are enabled solves optimally in less than 8 hours. It uses Gurobi 9.0's barrier method in an i7 processor with 6 cores, a RAM memory of 32 GB and a SSD enabled to share memory capacity for processing. The problem size is approximately 20 million variables, 25 million constraints, and 150 million non-zeros, resulting in 90 GB of maximum memory use.

[12] The model can represent any activity or energy carrier for different geographical scales. This is ideal for modelling regions, municipalities or clusters. However, this framework it is not practical for spatial oriented aspects or locational planning decisions, as there are better spatial-based solutions to deal with these types of problems [97].

presented to the model. Such a menu of options requires cost data and efficiency data to describe a technology, making technology learning a key model input. Simultaneously, the presence and operation of the aforementioned technologies create the need for energy in diverse forms, for which the model determines (also endogenously) the technological choice, installed capacities, and operation to supply them (also based on the inputted 'menu' of technological options). It is important to mention that the extent to which the system can adopt a technology is constrained by an assumed potential, making those potentials a key element of a scenario description. Finally, it is the operation of technologies to satisfy both driver and energy activities that generate emissions and the demand for primary energies, completing the required remaining panorama to determine the cost-optimal system configuration. A visualisation of the previously described conceptual framework is presented in Figure 13.

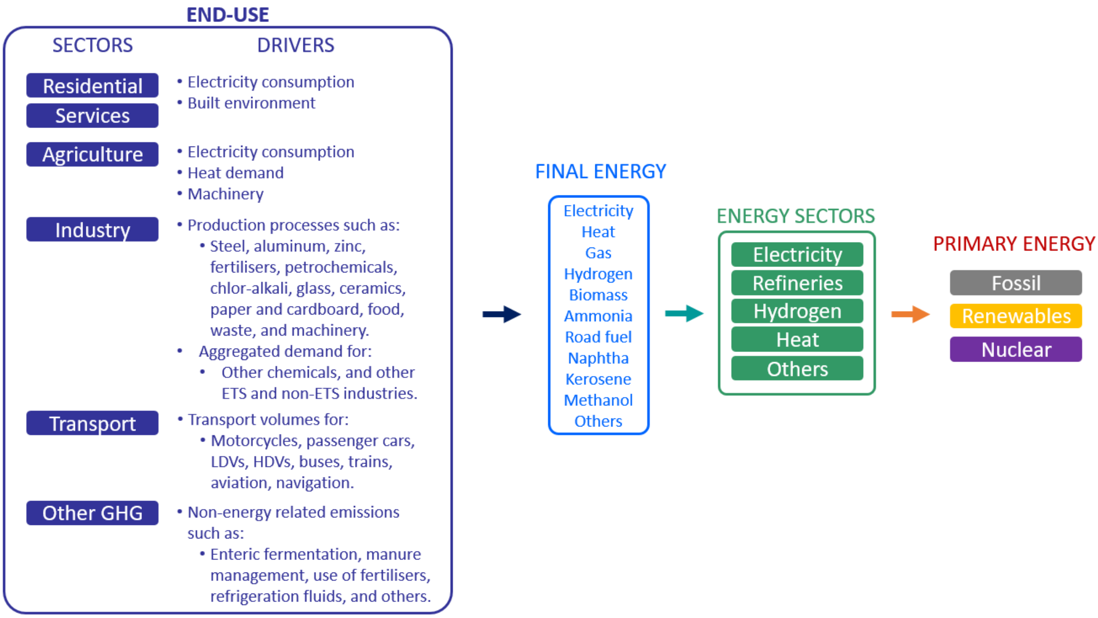

Figure 13, IESA-Opt conceptual framework.

As mentioned before, to provide cost-optimal planning towards complete system decarbonisation, IESA-Opt adopts very high sectoral, technological, and temporal granularities. This means that all the important energy-consuming activities are described in the model and that a large variety of technology options are considered to satisfy them. First, to explore cross-sectoral feedbacks (and coupling), it presents a sectoral bottom-up representation of standard and "low-carbon" options comprising biomass, CCUS, electrification and VRES, which result in a detailed description of considered activities and technologies. Then, the model considers hourly intrayear resolution, adequate to cope with the challenge presented by the adoption VRES [103]. Additionally, the latter requires that the model includes features that enable it to explore the roles that interconnected European power markets and flexibility alternatives play to further adopt VRES [104], [105]. Finally, the model also provides infrastructure descriptions such as pipelines and buffers for natural gas (LD, MD, HD), hydrogen (LD, HD), CCUS, and district heating and transmission lines and transformers for electricity networks (North Sea, LV, MV, HV). These descriptions help to account for costs and potentials to feasibly integrate VRES via their coupling with other energy carriers into the system, such as gas, hydrogen, or heat, and their possible synergies with CCUS [106], [107].

The linear formulation behind the representation of the above conceptualisation is presented in the following sections. Section 3.3 presents how to simultaneously integrate the operation of all sectors, activities, technologies, and emissions under one model and one objective function. Section 3.4 presents the formulation representing the evolution of technological stocks resulting from investment, decommissioning, and retrofitting decisions. The LP representation of the power dispatch (a key element of the energy system) is described in Section 3.5. Next, the formulation behind the flexible operation of technologies is presented in Section 3.6, where the most meaningful methodological contributions of the chapter can be found. Section 3.7 describes the operational constraints of gaseous networks. Finally, the representation of networks' infrastructure in the energy system can be presented in Section 3.8. All the model resources can be found at https://energy.nl/iesa/.

3.3. Sectoral integrated cost-optimised energy system towards decarbonisation targets

As described in the above presented conceptual framework, sectoral integration in IESA-Opt turns around two main axes, activities and technologies (analogous to the commodities and processes nomenclature in TIMES[108]). Thus, many technology use combinations can satisfy a desired volume of activities under a richly described technological landscape. The model simultaneously determines the optimal configuration and use of technologies to satisfy the required activities' volumes from such a broad domain. It minimises system costs resulting from the set of decision variables confirmed by use, investments, decommissioning, and retrofitting of technologies accordingly with the following expression[13].

[13] The first term represents the variable costs due to the use of the technologies; the second one, the investment costs resulting from investment decisions; the third one, the non-recoverable capital costs from premature decommissioning; the fourth one, the costs of retrofitting existing technologies; and the last one the fixed operational and maintenance costs of the technological stock.

$$\min\left[\sum_{t,p} u_{t,p}VC_{t,p} + i_{t,p}\alpha_t IC_{t,p} + d^{pre}{}_{t,p}DF_t\alpha_t IC_{t,p} + r_{t_i,t_j,p}\alpha_{t_j}RC_{t_i,t_j,p} + s_{t,p}FC_{t,p}\right] \qquad eq.(1)$$

Subject to ensure that the use of technologies meets at least the required exogenous activities drivers, as described by

$$\sum_t u_{t,p}AB_{t,a,p} \geq V_{a,p} \qquad eq.(2)$$

Additionally, subject to the available installed capacities of the technologies and the particular activity-to-capacity ratio for each technology, as shown in (3), Γ_t.

$$u_{t,p} \leq s_{t,p}\Gamma_t \qquad eq.(3)$$

Every single technology can affect one of the following emission-related activities considered in the model: CCUS network, national ETS, national non-ETS, external ETS, and international transport emissions. Most technologies increase the net volume of the emitting activity, and some technologies decrease it (such as carbon capture and direct air capture). To keep the emission activities balanced, four 'technologies' match their net account: CO_2 released to air in the national ETS, national non-ETS, external ETS, and international transport accounts. The emission constraint is therefore enforced by ensuring that the CO_2 released to air in the national ETS and non-ETS accounts does not exceed the national targets defined for the different periods as described by the following constraint:

$$\sum_{te} u_{te,p} \leq E_p \qquad eq.(4)$$

Nevertheless, it is important to mention that not all the sources of emissions considered within the scope of the targets are included within the activities covered by IESA-Opt. To be precise, approximately 85% of the emissions considered within the 2021 national inventory [109] are covered by the activities included in the energy system framework; then, for the remaining 15% (mostly agricultural activities), a less detailed approach is used. Here, the emissions resulting from activities such as enteric fermentation, manure management, use of fertilisers and use of refrigeration fluids are input to the model as driving activities. Their potential reductions and costs are addressed with MACC curves (extracted from the IMAGE model database [110]). A complete description of the methodology is provided in Appendix A.

3.4. Transition path

The transitional capability of the model derives from the fact that it can plan for the optimal system configuration for the different periods covered in the transition, at the same time that it determines the optimal intra-year operation of the stocks. The transitional elements are described by the investment, premature decommissioning, and retrofitting decisions that give shape to the technological stock accordingly with the following formulation:

$$s_{t,p} = s_{t,p-1} + i_{t,p} + r_{t^i,t,p} - r_{t,t^i,p} - ({d^{cum}}_{t,p} - {d^{cum}}_{t,p-1}) \qquad eq.(5)$$

being:

$${d^{cum}}_{t,p} = {d^{cum}}_{t,p-1} + {d^{pre}}_{t,p} + {d^{lt}}_{t,p} \qquad eq.(6)$$

It is important to ensure that premature decommissioning can freely happen at any convenient period but avoid decommissioned technologies that cannot be decommissioned in a year and recommissioned back in a subsequent period. Simultaneously, the model must be able to address the costs of premature decommissioning. For this purpose, the following constraint together with (5) and (6) ensures that both requirements are satisfied:

$${d^{cum}}_{t,p} \geq {d^{cum}}_{t,p-1} \qquad eq.(7)$$

Additionally, as part of the scenario descriptions, some technologies are defined within a certain deployment bandwidth. This same constraint, depicted in (8), sets the adoption potentials for technologies and caps system emissions.

$${S^{min}}_{t,p} \leq s_{t,p} \leq {S^{max}}_{t,p} \qquad eq.(8)$$

Last, the retrofitting of technologies is constrained by the available stocks of the original technology and by an input binary parameter that determines which are the possible retrofitting relations. This results in the following formulation:

$$r_{t_i,t_j,p} \leq s_{t,p-1} RM_{t_i,t_j} \qquad eq.(9)$$

3.5. European hourly power sector dispatch

Modelling power dispatch within ESOMs asks for choices to be made to avoid enormous computational requirements. First, the study [111] concluded that poor temporal resolutions negatively affect outcome reliability for scenarios with moderate and high presence of VRES and greatly recommends prioritising using at least hourly resolution. Additionally, adopting a sequential description of the power dispatch enables us to retain the chronological order in the variability of the events, which is key for short- and long-term storage technologies. Thus, IESA-Opt adopted an hourly resolution of the complete year operation (8760 sequential points per year).

Furthermore, the same study [111] also mentions that operational detailing, namely, unit commitment, increases reliability as the presence of VRES starts to increase. However, it also states that adopting unit commitment loses relevance after a certain level of VRES penetration, as fewer thermal units affect the system dynamics. This observation is further reinforced by another study that states that MIP unit commitment performs better in scenarios with a low presence of VRES, but for scenarios with high levels of VRES, an LP approach suffices to provide reliable results [101]. Additionally, there is plenty of evidence that increasing the geographical scope of the model to consider European cross-border interactions has a significant impact on the outcome reliability of the models [2], [112]. Therefore, in this model, we exclude the unit commitment formulation (MIP) and rather include the whole European power system represented in 20 nodes (see Appendix C). This penalises the ability of the model to reliably analyse low VRES scenarios with a high presence of thermal generators (as unit commitment is excluded), but keeping the convenient LP formulation enables IESA-Opt to simultaneously solve the EU power dispatch and the integrated national energy system within the same formulation while considering a high temporal resolution and a moderate and high presence of VRES. Thanks to such modelling choice, it is possible to analyse the interaction of storage, flexible demand technologies, VRES, and cross-border interconnection within the sector-coupled energy system of the Netherlands.

The following linear formulation is used to include the previously described concepts within the IESA-Opt framework. First, the fundamental constraint that the electricity supply and demand must remain balanced every hour is included. For this purpose, we divide technologies into five main groups: dispatching technologies, t_d, technologies with flexible, t_{pf}, and nonflexible operation, t_{pn}, flexible CHPs, t_c, and shedders, t_s. For each of the 24 different electricity networks considered in the model, conforming to the set A^e, the hourly balance is represented with the following constraint:

$$\begin{aligned} u_{h,td,p}AP_{td,a,p} = {} & u_{t_p,p}P_{h,tp}AB_{tp,a,p} + (\Delta q^{up}{}_{h,tf,p} + \Delta q^{dw}{}_{h,tf,p})AE_{tf,a} + (u_{tc,p}P_{h,tc} \\ & + \Delta u_{h,tc,p})AB_{tc,a,p} + \Delta p_{h,tc,p}AE_{tc,a} + (u_{ts,p}P_{h,ts} \\ & + \Delta u_{h,ts,p})AB_{ts,a,p} \qquad \forall\, a \mid a \in A^e \qquad eq. (10) \end{aligned}$$

This equation can be read as supply is equal to reference hourly demand, plus flexible demand variations ($\Delta q^{up}{}_{h,tf,p}$ and $\Delta q^{dw}{}_{h,tf,p}$), plus the bidimensional CHP flexibility variations ($\Delta u_{h,tc,p}$ and $\Delta p_{h,t_c,p}$), and the shedding demand variations ($\Delta u_{h,ts,p}$), for each interconnected node. These three forms of flexibility are further explained in section 3.6.

Another major determinant for the dispatch of electricity is resource availability, and this turns relevant for two reasons: the installed capacities of generation technologies and the intermittency of renewable energy sources. Every technology in the model is described with an hourly operation $P_{h,t}$. For the dispatching technologies, this profile represents the hourly availability of the resource, and for the other technologies, it represents the hourly reference operation[14]. The availability of VRES resources can substantially impact the energy system outcome[113]; hence, the ability of the model to easily modify the profile of any technology in the system is a significant characteristic. The following constraint ensures that supply occurs according to the existing installed capacity and to the extent to which hourly resource availability allows it:

$$u_{h,td,p} \leq s_{td,p}\Gamma_{td}P_{h,td} \qquad eq. (11)$$

Additionally, ramping constraints are considered for dispatchable generation according to the following constraint:

$$-R_{td,p}^{dw} \leq \left(u_{h,td,p} - u_{h-1,td,p}\right) \leq R_{td,p}^{up} \qquad eq. (12)$$

Losses occurring during the transport process are accounted for only when energy is "transferred" from one network to another by a capable technology (connector, transformer, compressor). Hence, the formulation does not account for losses proportionally to travelled distance under a specific voltage level and cable type. The formulation of the considered losses is implicitly modelled in the energy balance of the technology and therefore driven by the use of such technology.

Last, the European representation, the dispatch architecture, the data on profiles and operational parameters are strongly based on the same modelling structure used as input by the COMPETES model [114]. Further details can be found in Appendix B.

[14] The profiles are normalized and extracted from historical datasets such as the wind and solar availability in the Netherlands and the other 20 considered EU regions; the load profile of the Netherlands and EU regions; reference EV charging and connection profiles; temperature profiles; and a flat profile. Due to availability of data, thus far only 84 hourly profiles have been included, but every technology is assigned to one of them, which means that many technologies share profiles. However, if more data becomes available the model is already enhanced to easily include it into the database, and would not result in increased computational times.

3.6. Hourly flexible operation in coupled sectors

In addition to the power dispatch description, representing possible deviations from reference hourly operation profiles is paramount for the dispatch and adequately represents sector coupling. With this aim, IESA-Opt considers three types of intrayear operational decisions: flexible CHPs, shedding technologies, and demand technologies with flexible operation.

3.6.1. **Flexible CHP's**

CHPs are modelled as operation technologies, which means that their hourly operation profile is fixed, and the changes in their use affect such profiles proportionally. However, some CHPs, known as extraction-condensing steam turbines, can extract a fraction of the condensed steam before (or during) the expansion phase (the power turbine) to be used to provide heat [115], [116]. Such enhancement allows these turbines to adjust their power-to-heat ratio, which, combined with the amount of steam generated before the expansion, gives the technology a huge potential to modify its power and heat outputs and fuel inputs to adapt to electricity price events (among other externalities) [117]. The resulting bidimensional flexibility (the fuel inputted into the boiler and the extraction flow of the condensed steam) is considered by IESA-Opt using a convenient LP simplification (resembling other ESMs [118]).

In a linear representation of a flexible CHP, the fuel requirement, F, is assumed to be determined by the heat and power outputs, H and P, accordingly with $F = {}^{H}/_{\eta} + {}^{P}/_{\varepsilon}$. where η and ε represent the CHP efficiencies when producing only heat and power, respectively. For this, IESA-Opt considers two dimensions of flexibility: the hourly deviations in the fuel input representing the deviations in use, $\Delta u_{h,t_c,p}$, and the hourly deviations in the power output, $\Delta p_{h,t_c,p}$. This leads to the following constraint to ensure that the heat demand provided by the CHP is satisfied in a specific time window:

$$\sum_{h \in TW_{tc}} \left[(u_{tc,p} P_{h,tc} + \Delta u_{h,tc,p}) AB_{tc,a,p} - {}^{\eta_{tc}}/_{\varepsilon_{tc}} \Delta p_{h,tc,p} \right] = \sum_{h \in TW_{tc}} u_{tc,p} P_{h,tc} AB_{tc,a,p} \qquad eq. (13)$$

3.6.2. **Shedding technologies**

The upcoming energy transition will deliver a set of technologies that could provide sector coupling via the conversion of electricity into other energy forms (such as heat [119], hydrogen [120], methanol [121], methane [122], hydrocarbons [4], chlorine [123], ammonia[124], and other chemicals [125]) via technologies such as heat pumps or electrolysers. Additionally, some industrial processes (such as electrified steel production, aluminium smelters, and paper pulp mills) can stop or lower their activity level to adapt to power market dynamics. We use word shedding to refer to the action taken by all of the abovementioned technologies of cutting down operations in a critical hour to decrease electricity consumption and help to alleviate the system. This opens the door to foreseeable scenarios where these technologies could be interruptedly operated to avoid high electricity price events and decrease operational costs [125]. However, extra capacity must be installed to satisfy demand while sacrificing operational times [126]. In summary, shedding technologies in IESA-Opt can selectively operate in specific hours in exchange for overinvestments.

The representation of these technologies in the model assumes they can shed their hourly activities using an hourly decision variable that represents the decrease in use for each hour. This variable is capped by the installed capacity of the technology, as shown below:

$$\Delta u_{h,ts,p} \leq s_{ts,p} SC_{ts} UtP_{ts,p} \qquad eq.(14)$$

Because, as stated in (2), the model must ensure sufficiency in the activities balances, it will determine the required technological stock, determining the necessary excess capacity to cope with such shedding.

Furthermore, technologies might not have a flat operational profile and might be subject to specific sectoral dynamics, or perhaps a certain technology may require a minimum level of operation, such as heat pumps with seasonal heat storage or P-to-X in industry. For these cases, shedding will occur between the reference operational profile and the minimum required load described by the maximum allowed shedding fraction as imposed by the following constraint:

$$\Delta u_{h,ts,p} \leq u_{ts,p} P_{h,ts} SF_{ts} \qquad eq.(15)$$

where SF_{t_s} represents the assumed potential shedding fraction of each shedding technology. The profile is flat for technologies without specific sectoral dynamics.

3.6.3. **Conservative flexibility**

The last element presented here consists of the formulation used for technologies that allow for deviations in the reference profile without compromising the technology output and with or without paying an efficiency penalty. We call these options conservative flexibility, as all the up or down flexibility must eventually be recovered with an action in the opposite direction. Some examples of these technologies are residential and service appliances such as dishwashers, washing machines, fridges or freezers [90], [127]; electric heating appliances with active or passive storage [128]–[130]; electric vehicles with smart charging or vehicle-to-grid enhancements [131]; industrial processes with opportunities for flexible programming of their operations [90], [132]–[134]; and various kinds of batteries and storage technologies [135]–[137], [137].

To model such a vast group of technologies, they were grouped into 4 different archetypes: load shifting for typical demand response and active thermal storage; smart charging of electric vehicles; vehicle-to-grid; and storage technologies. Each of these groups is represented under a specific formulation in the model and can be applied to all technologies considered under each category. However, all formulations share three elements in common: a balance constraint, a capacity constraint, and a saturation constraint, and each of the elements is interpreted differently for each archetype. It is important here to mention that these 4 archetypes refer only to the fundamental constraints ruling the behaviour of the different conservative flexible technologies; however, the technologies in the model are explicitly included (i.e., each flexible technology is independently accounted for in the model).

The energy balance states that the net energy demand should remain constant for the considered time window, and the use of time windows is adopted to maintain a linear formulation of the balance. This implies that the net balance of the upwards and downwards gross shifted load within the time window should be equal to the corresponding losses, if any, as follows:

$$\sum_{h \in TW_{tf}} \Delta q^{up}{}_{h,tf,p} + \sum_{h \in TW_{tf}} \Delta q^{dw}{}_{h,tf,p} = \sum_{h \in TW_{tf}} l_{h,tf,p} \qquad eq.(16)$$

Both upward and downward shifts are subject to a physical capacity constraint determining the minimum and maximum boundaries of the feasible rescheduling capacity. For instance, this constraint in flexible heat pumps sets the maximum available upward shift equal to the difference between the reference profile and the heat pump's maximum capacity. These limits can be asymmetrical to each other and can be hourly variables. This second element is illustrated in the two following equations:

$$\Delta q^{up}{}_{h,tfp} \leq \Delta q^{max}{}_{h,tf,p} \qquad eq.(17)$$

$$\Delta q^{dw}{}_{h,tf,p} \geq \Delta q^{min}{}_{h,tf,p} \qquad eq.(18)$$

Finally, a saturation constraint ensures that the shifted volume does not violate a feasible operational limit, such as the storage capacity of an active storage unit or a latent heat requirement of a built environment system. These saturation limits can be either fixed or represented by a combination of parameters and variables depending on the archetype involved; therefore, the third type of constraint follows the structure below:

$$v^{min}{}_{h,tf,p} \leq \sum_{h \in TW_{tf}} \left[B^{up} \Delta q^{up}{}_{h,tf,p} + B^{dw} \Delta q^{dw}{}_{h,tf,p}\right] \leq v^{max}{}_{h,tf,p} \qquad eq.(19)$$

B^{up} and B^{dw} are two conceptual binary parameters used to illustrate that the saturation constraint can be imposed independently on both shift directions.

The interpretation of these three forms of constraints is presented below for all 4 presented archetypes.

Demand Response

This form of flexibility assumes that the installed capacity of the technology caps the application of flexibility. This directly affects the capacity constraint interpretation, stating that the maximum upward deviation available is given by the difference between the installed capacity and the use of the technology determined by the hourly profile in the following way:

$$\Delta q^{up}{}_{h,tf,p} \leq (s_{tf,p}FC_{tf} - u_{tf,p}P_{h,tf})AE_{tf,a} \qquad eq.(20)$$

and the maximum upward deviation is given by the ability of the technology to decrease its hourly consumption given by

$$\Delta q^{dw}{}_{h,tf,p} \leq (1 - NN_{tf})u_{tf,p}P_{h,tf}AE_{tf,a} \qquad eq.(21)$$

The volume constraint ensures that the reallocated energy consumption within a time window does not exceed the original total consumption of the time window, upwards or downwards, as shown below.

$$\sum_{h \in TW_{tf}} \Delta q_{h,tf,p} \leq \sum_{h \in TW_{tf}} u_{tf,p}P_{h,tf}AE_{tf,a} \qquad eq.(22)$$

Storage

The (dis)charging capacity gives the interpretation of the capacity constraint for storage. The maximum amount of flexibility that any storage technology can provide is determined by the following constraint:

$$\Delta q_{h,tf,p} \leq s_{tf,p}CC_{tf} \qquad eq.(23)$$

The interpretation of the volume constraint for storage is marked by the storage capacity as described by the theoretical charging time of a battery according to the following constraint.

$$\sum_{i \leq h} \Delta q_{i,tf,p} \leq s_{tf,p}CC_{tf}CT_{tf} \qquad eq.(24)$$

Smart Charging and Vehicle-to-Grid

The main characteristic of these forms of flexibility is that they are dependent on the number of vehicles connected to the grid at a given moment. Thus, the upward capacity is capped by the difference between the charging capacity of connected EVs and the reference charging profile as given by:

$$\Delta q^{up}{}_{h,tf,p} \leq CC_{tf}\left(s_{tf,p} - \frac{u_{tf,p}VU_{h,tf}}{AS_{tf}}\right) - u_{tf,p}P_{h,tf}AE_{tf,a} \qquad eq.(25)$$

The downwards flexibility is constrained by the reference consumption [15] and the non-negotiable load for smart charging:

$$\Delta q^{dw}{}_{h,tf,p} \leq (1 - NN_{tf})u_{tf,p}P_{h,tf}AE_{tf,a} \qquad eq.(26)$$

By the discharging capacity of connected vehicles for vehicle-to-grid flexibility:

$$\Delta q^{dw}{}_{h,tf,p} \leq DC_{tf}\left(s_{tf,p} - \frac{u_{tf,p}VU_{h,tf}}{AS_{tf}}\right) \qquad eq.(27)$$

The volume constraint for both smart charging and V-to-G is given similarly to storage, where the cumulative application of flexibility cannot exceed the difference between the available storage capacity of connected vehicles and the minimum required stored energy for the journeys of the vehicles departing in that hour given by:

$$\sum_{i\leq h} \Delta q_{i,tf,p} \ \leq CC_{tf}CT_{tf}\left(s_{tf,p} - \frac{u_{tf,p}VU_{h,tf}}{AS_{tf}}\right) - \sum_{h\leq i\leq h+AJ} u_{tf,p}P_{i,tf}AE_{tf,a} \qquad eq.(28)$$

3.7. Operation of gaseous networks

Integrated electricity and gas models usually focus on designing a proper nodal representation of the network based on pressure tolerances and Bernoulli equations, intending to provide detailed planning and operation optimisation [138]. Because of the large scope of the problem and specific goals of the methodology, IEM often ignores any detailed description of the gas system. However, because we aim to address seasonality, buffer opportunities, and infrastructure costs, IESA-Opt includes a simplified

[15] The EVs reference consumption is an input data that can easily be changed to explore different scenarios. Currently, the reference charging profile is based on the standard pattern in which EV users connect their vehicles to charge right after their journey, resulting in the characteristic “two-spike” profile. Similarly, the EV’s usage profile is also provided as input data.

representation of gaseous network operation based on a daily balance dispatch approach [139]. This representation is presented below.

Gas networks, as transporters of a compressible fluid, are inherently provided with a buffer that allows for damping (i.e., the temporal discoordination between the input and output flows to the gas network) [139]. However, the operation of the network must occur within safety pressure boundaries, meaning that the size of the buffer has limits (and regions), thus requiring intraday balancing actions to keep networks functional[16]. There is no specific balancing period in this scheme. The imbalances are corrected when the magnitude of the imbalance reaches a certain predefined level [140].

A daily balancing approach was selected for activities distributed by the network of gaseous pipelines. This approach was selected first due to the previously described damping characteristic and second due to a typical daily flat price profile resulting from models with the hourly balancing of gas dispatch [141]. Such modelling choice allows for dispatching national wells and imports, considering the daily operation of the buffers (e.g., gas storage chambers), and describing other generation processes with particular sectoral dynamics such as fermentation, (bio)gasification, and methanation[17]. However, this representation cannot provide network planning or operation of circulating compressors. Finally, the same approach is used for all the gas transported in pipelines: natural gas (HD, MD, and LD), hydrogen (HD and LD), and sequestered carbon dioxide for CCUS.

Similar to the electric balancing description, the gas dispatch is described for each day accordingly with:

$$u_{d,td,p}AB_{td,a,p} = u_{tp,p}P_{d,tp}AB_{tp,a,p} + (\Delta q^{up}{}_{d,tg,p} + \Delta q^{dw}{}_{d,tg,p})AG_{tg,a} \qquad eq.(29)$$

Additionally, the daily dispatch technologies, analogous to the power dispatch, are bounded by their daily availability profiles and installed capacities accordingly with:

$$u_{d,td,p} \leq s_{td,p}\Gamma_{td}P_{d,td} \qquad eq.(30)$$

3.8. Networks' infrastructure description

The infrastructure of the networks imposes a limitation on the system in terms of the extent to which an activity can be carried out within a certain time frame and geographical

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[16] There are different types of balancing actions designed accordingly with the size of the imbalance. As reference of the magnitude, no balancing action is required for hourly imbalances of ~2% of the daily market volume. In average, 3 balancing actions per day were required between November 5th 2019 and December 4th 2019 [139] (high demand season).

[17] Methanation, as an electricity consumer, is already subject to hourly shedding constraints (section 3.6.2). Thus, the daily gas dispatch formulation further restricts its operation.

area. This restriction provides an extra incentive for flexibility, as it can avoid network reinforcement costs [138]. Furthermore, these infrastructure descriptions help to better represent the expected transitional costs, as the energy system must adapt to enable the deployment of infrastructure-intensive technologies, such as CCUS, hydrogen, and district heating. The infrastructure representation adopted in IESA-Opt is presented in Table 11.

Technology	Activity	Time frame
Final natural gas HD grid pipeline	HD Final natural gas	1 day
Final natural gas MD grid pipeline	MD Final natural gas	1 day
Final natural gas LD grid pipeline	LD Final natural gas	1 day
Hydrogen HD grid pipeline	HD Hydrogen	1 day
Hydrogen LD grid pipeline	LD Hydrogen	1 day
CCUS grid pipeline	CCUS	1 day
HV Electricity grid cable	HV Electricity	1 hour
MV Electricity grid cable	MV Electricity	1 hour
LV Electricity grid cable	LV Electricity	1 hour
LT Heat distribution network pipeline	LT Heat distribution network	1 hour

Table 11. Considered infrastructure technologies in IESA-Opt.

As shown in Table 11, the activities constrained by available infrastructure are described with daily and hourly timeframes. For the hourly ones, infrastructure limits the volumes of the activity in a time frame accordingly with:

$$(u_{t,p}P_{h,t} + \Delta u_{h,ts,p})AB_{t,a,p} + (\Delta q^{up}{}_{h,tf,p} + \Delta q^{dw}{}_{h,tf \mid tf \neq tf_b,p})AE_{tf,a} \leq s_{ti_h,p}\Gamma_{ti_h}$$

$$\forall\, a \mid a \in A^e \;\&\; \forall\, t \mid AB_{t,a,p} > 0 \qquad eq.(31)$$

Similarly, the model considers the following constraint for the daily described infrastructure technologies, t_{i_d}:

$$(u_{tp,p}P_{d,tp} + \Delta u_{h,tc,p} + \Delta u_{h,ts,p})AB_{tp,a,p} + (\Delta q^{up}{}_{d,tf,p})AG_{tf,a} \leq s_{ti_d,p}\Gamma_{ti_d}$$

$$\forall\, a \mid a \in A^g \;\&\; \forall\, t \mid AB_{t,a,p} > 0 \qquad eq.(32)$$

Other elements of the energy infrastructure, such as transformers and buffers, are considered operational technologies. Thus, this formulation does not represent these technologies as it only refers to infrastructure that exerts no action other than enabling the flow of an activity to a certain volume.

Modelling of decarbonisation transition in national integrated energy system with hourly operational resolution [18]

Abstract

In this chapter, we present an optimisation integrated energy system model (IESA-Opt) for the Netherlands with the use of a linear programming formulation. This state-of-the-art model represents a scientific contribution as it integrates a European power-system model with a complete sectoral representation of the energy system technologies and infrastructure that account for all greenhouse gas emissions considered in the targets, and takes into consideration a detailed description of the cross-sectoral flexibility (e.g. flexible heat and power cogeneration, demand shedding from power-to-X and electrified industrial processes, short- and long-term storage of diverse energy carriers, smart charging and vehicle-to-grid for electric vehicles, and passive storage of ambience heat for the built environment). This model provides a detailed description of the operation of technologies and considers exogenous technological learning to simultaneously solve multi-year planning of investments, retrofitting, and economical decommissioning with intra-year operational, flexible, and dispatch decisions. The model is applied to a case study of the Netherlands energy transition under the current climate policy and conservative projections for the economy and availability of resources. The results present a significant reliance on renewable energy sources, such as wind (800 PJ) and solar (300 PJ), to fuel the electrification revolution as well as biomass (550 PJ) for feedstock and heat purposes coupled with carbon capture, utilisation, and storage (CCUS) to achieve negative emissions in certain sectors. However, oil (880 PJ) and gas (1050 PJ) constitute almost half of the final energy demand as they are required for heat applications, industrial feedstock, refined oil products for export, and international transport fuel. Four different sensitivity analyses are presented for the emission reduction target, oil demand streams, biomass availability, and demand volumes. The most significant findings are as follows: 1) it is crucial to have simultaneous highly available biomass and CCUS storage capacities to achieve negative emissions and facilitate the transition; 2) even in a highly decarbonised scenario, it is necessary to simultaneously develop climate policies focused on international transport emissions, oil-based feedstock, and refined-oil product exports to completely displace oil from the energy mix; 3) (imported) biomass has the ability to decrease system costs (3% under conservative scenarios of availability and price); however, for biomass prices higher than 20 €/GJ, this effect is lower; 4) in relative terms, the system is most sensitive to demand uncertainties from the transport sector than any other sector, followed closely by the industrial sector.

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4.1. Introduction

Following the EU 2030 Climate and Energy Framework [142], the Netherlands is required to reduce its greenhouse gas (GHG) emissions by 49% by 2030, compared to its 1990 levels, and realise a 95% reduction by 2050[19] [143]. The overall focus of the Dutch energy transition pathway in the coming decades is towards decarbonisation, energy efficiency, and system integration [144], notably through the increase in renewable electricity production and the conversion of 'green electrons' into 'green molecules' [145]. Higher levels of electrification in various sectors increases the need for further sector coupling and system integration. The use of this highly electrified energy system, which is mainly supplied by variable renewable energy sources (VRES), results in a greater need for flexibility in the energy system as a whole and the power system in particular [90]. However, it should be noted that the future layout of the energy system and energy mix is still uncertain, and complex methodologies are required to evaluate its possibilities.

One of the most accepted methods of analysing the transition towards the described energy system requires the application of high-resolution energy system models (ESMs) for addressing the implications of VRES on the energy system. For instance, optimisation ESMs have been extensively used in the energy modelling community; however, they have their respective shortcomings. With a focus on national models that consider all the energy sectors and GHG emissions, Fattahi et al. proposed a list of capabilities required by ESMs to address the challenges raised by the increasing share of VRES, and the resulting complexity and required system integration [98]. They synthesised the challenges into six categories, intermittency and flexibility, further electrification, new technologies and technological change, decentralisation, human behaviour, and macroeconomic interactions, and proposed a conceptual framework for addressing them, as presented in Figure 14. For European countries, such as Germany and the Netherlands, this framework is built around a central national ESM containing or linked to a European energy-market model and can be easily linked with a regional model.

[19] The GHG-emission reduction objectives are often reviewed by the European Commission and national governments; therefore, in this study, we use the official intentions of the Dutch government until January 2021. However, the targets are likely to become more stringent in the upcoming years.

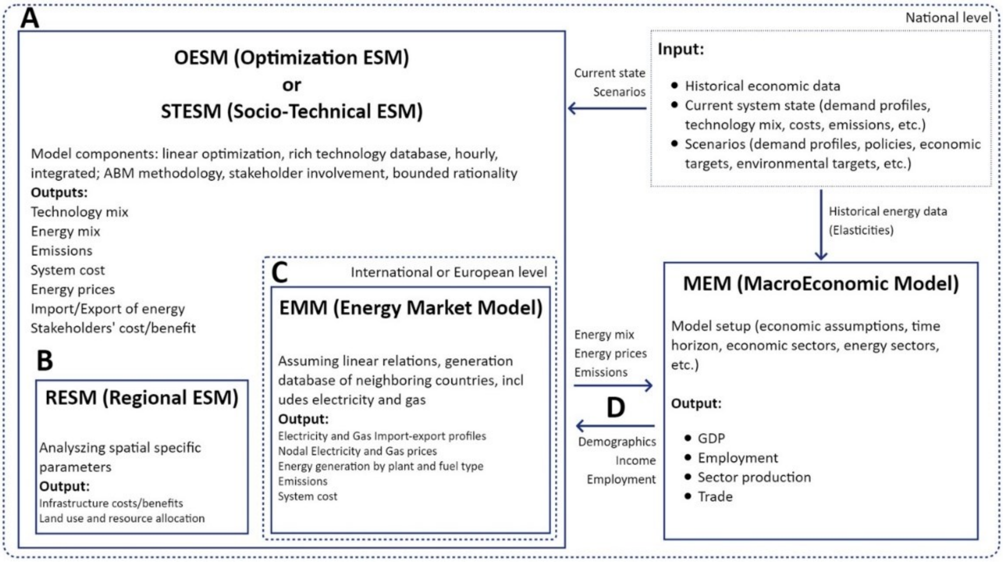

Figure 14, Optimisation integrated ESM (IESA) framework presented by Fattahi et al. [98].

Fattahi et al. [98] also performed a broad multi-criteria analysis (Appendix A) over an extensive literature review of existing ESMs, highlighting the need for an improved modelling approach. Among these ESMs, there is currently no model that simultaneously includes the following essential capabilities for addressing the aforementioned challenges: hourly temporal resolution, European power dispatch, multi-period investment optimisation, complete representation of the energy system with an accounting of the GHG emissions included in the climate policy targets, complete technological representation of activities within each sector while taking into consideration (exogenous) efficiency improvements and (exogenous) technological learning, and an appropriate account of the costs of the infrastructure transformation. Some of these capabilities, such as the consideration of a number of periods, interconnection within the European power system, or flexibility and infrastructure representations, can have a major impact on the modelling outcome, as presented in [100]. Furthermore, it should be easily possible to integrate the model with other tools to provide linked approaches for addressing the energy transition complexities from broad and synchronised perspectives.

For example, the integrated MARKAL–EFOM1 (market-allocation–energy-flow-optimization-model) system (TIMES) model [91] provides a detailed techno-economic representation of all the energy sectors, sector coupling technologies, and infrastructural limitations, while using 'integral'[20] time slices instead of an hourly temporal resolution. The use of aggregated time slices is an overestimation of the potential contribution of large base-load power plants and underestimation of the need for supply–demand management and storage with high shares of VRES [92]. In a manner similar to TIMES, OPERA provides a detailed techno-economic representation of the energy system [146]; however, it lacks optimal multi-year investment decisions [93]. Neglecting the multi-year optimisation undervalues the role of the current technological stock and its techno-economic lifetime on the system costs. Python for power system analysis (PyPSA) provides an open-access ESM that emphasises power-network details such as the physics of power flow according to the impedances in the network [94] at the expense of a simpler technological representation of other sectors. It has been communicated on the PyPSA-Eur-Sec website that the model is being expanded to take into account all the emissions considered in the targets. Nevertheless, on top of it being not published yet, its representation of non-power sectors is being simplified and does comprise perfect foresight for planning nor endogenous investments in industrial processes[21]. Similarly, COMPETES provides a detailed representation of the European power-sector dynamics for operation and planning decisions, and it is well suited to flexible demand technologies [147]. However, it is focused on the power system and does not include all sectors and activities related to the decarbonisation targets. Compared to other ESMs, OseMOSYS requires less time for computation and no upfront financial investment as it is an open source modelling system; however, it does not account for high technological resolution and infrastructure constraints [95]. REMix uses the EnDAT tool [39] to pre-process the heat and power-demand data for incorporating geospatial variations in the hourly optimisation model [96], but the model and its database are not publicly accessible to this date, and many sectoral activities are excluded from the scope of the model. As indicated in Table 12, none of these models has all the capabilities required to address the aforementioned modelling challenges. Therefore, the development of a new model that simultaneously satisfies all these capability requirements is necessary.

This study presents a new model called the integrated energy system analysis optimisation (IESA-Opt) model, which facilitates the harmonised and combined use of (future) simulation, regional, and macroeconomic-focused analyses as part of the IESA modelling framework for the Netherlands. This linear programming (LP) model simultaneously provides all the capabilities listed in Table 12, as it can solve the short-term hourly operation and long-term 5-year-interval planning problem from 2020 to 2050 (with the

[20] Approximate the (residual) load duration curve by dividing a year into a limited number of time slices (typically 4–12) to represent seasonal, daily, and diurnal variations in demand and supply [304].

[21] We are looking forward to the updated release, as we are certain that when PyPSA-Eur-Sec is further developed to the ambitions mentioned in their website, a great opportunity to make a collaborative use of both models will arise.

possibility of extending the time horizon). Furthermore, the model includes multi-year techno-economic data of more than 700 technologies in all sectors for both energy transformations (i.e. electricity, refineries, heat, hydrogen, gas, and biomass) and final demand (i.e. residential, services, agriculture, transport, and industry). In this rich technological representation, cross-sectoral technologies are included, such as P2Heat, P2Gas, P2Hydrogen, P2Liquids, P2Mobility, and V2Grid, as well as the corresponding descriptions of their flexible hourly operation. Exogenous technological learning, efficiency improvements, and decommissioning and retrofitting parameters are also included in the formulation. To model the implications of hourly import and export of electricity on the Dutch energy system, IESA-Opt comprises an hourly electricity dispatch of EU countries with 20 nodes, each with their own hourly load, specific hydro storage capacity, onshore wind, offshore wind, and solar profiles. In addition to GHG emissions related to the energy system (divided into emissions within and outside the emission trading scheme (ETS)), the model also takes into consideration the emissions from non-energy sources, such as enteric fermentation, fertilisers, manure management, and refrigeration fluids. To address the network buffer capacity, IESA-Opt represents the operation of gaseous networks [139] based on a daily balance dispatch [140]. The energy infrastructure is modelled in ten networks for different voltage levels of electricity and different pressure levels of natural gas, hydrogen, and CCUS, as well as for the distribution of district heating.

Model	**Modelling Capabilities**						
	Hourly resolution	European power dispatch	Multi-year investment optimisation	Complete energy system representation	High technological resolution	Infrastructure representation	Accessibility
TIMES [91]		Y	Y	Y	Y	Y	Medium
OPERA [93]				Y	Y	Y	Medium
COMPETES [147]	Y	Y	Y		Y	Y	Low
PyPSA [94]	Y	Y				Y	High
OseMOSYS [95]		Y	Y				High
REMix [96]	Y	Y	Y			Y	Low
IESA-Opt	Y	Y	Y	Y	Y	Y	High

Table 12, Modelling capabilities of reviewed ESMs.

One of the objectives of developing IESA-Opt is to provide a low entry barrier (i.e. transparent) model that requires no upfront financial investment (to purchase specialised licenses) for academic research. In addition, owing to the enormous size of the optimisation problem, there is a need for efficient computing software that is commercially available. Therefore, two commercial software packages with a free academic license are selected to maximise the computational efficiency and accessibility of the model. IESA-Opt is implemented in the commercial AIMMS software [148], which uses an algebraic modelling language, such as GAMS, AMPL, and MPL. The GUROBI mathematical optimisation solver [149] is used to solve the LP problem in parallel central processing unit cores[22]. Moreover, to expand the accessibility of the model and its results, the results of the model are visualised using a web-based user interface that is realised in the R programming language [150]. The model's source code and its database are available online through the model's web user interface[23] [151].

The main research objective of this study is to develop a method of analysing the impact of cross-sectoral flexibility in an integrated energy system of the Netherlands to accommodate large amounts of variable renewable electricity. The method of transitioning the energy system for taking into consideration the interactions of energy usage, emissions, and costs also needs to be determined. To better explain these objectives, the main contributions of this study are presented as follows:

- It presents a multi-sector ESM that simultaneously considers hourly power dynamics, integrates the European power dispatch, uses multi-year optimisation, includes all sectors of the energy system with a complete emissions inventory, adopts a rich technological description, and represents system infrastructure costs and potentials.
- It applies the IESA-Opt model in an optimisation case study of the Netherlands energy transition and presents and analyses the results after making use of the aforementioned modelling capabilities, such as exogenous technological learning; hourly dispatch of the European power system, investment, retrofitting, and economic decommissioning decisions; cross-sectoral flexibility dynamics; gaseous infrastructure network flows and seasonality; and a complete inventory of GHG emissions in the system.
- It uses the practical modelling framework to perform sensitivity analyses to understand the implications of biomass and CCUS in achieving negative emissions; explores the roles of the various demand streams for oil; analyses the impact of biomass availability and its cost in the transition; and quantifies the uncertainty of key demand volumes for different sectors.

In addition to scientific contributions, this work provides a transparent and accessible modelling framework that can be adopted by different audiences for diverse purposes. The model code and database are open access and are available online. Owing to this and

[22] https://www.gurobi.com/resource/parallelism-linear-mixed-integer-programming/

[23] https://www.energy.nl/iesa. This paper describes version 3.06 of IESA-Opt. Please note the version number for accessing the model's web portal.

the modular structure of the model, it is suitable for diverse transdisciplinary applications (such as macroeconomic, behavioural, or regional analyses), and it is built such that, by simply modifying the database, the model can be used to study other countries or systems of interest. These features make the model ideal not only for its purpose within the IESA framework, but also for integration with any other framework in the academic community.

The remainder of this chapter is organised as follows. In Section 2, we provide an overview of the IESA-Opt formulation and introduce the scenario used for the case study. Section 3 describes the key results of the scenario analysis, which is followed by a sensitivity analysis presented in Section 4.4. After the conclusion presented in Section 4.5, supplementary materials are presented in Appendices.

4.2. Methodological approach

To provide an analysis of the Netherlands energy transition while considering the operational impact of VRES and cross-sectoral flexibility among the integrated energy sectors, this study presents the IESA-Opt model and illustrates its capabilities using the case study of the energy transition in the Netherlands. This section presents the methodological foundations of the IESA-Opt model and the general scenario used for the case study. Further details regarding the model methodology can be found on the model website.

4.2.1. **IESA-Opt framework**

To better present the framework, we divide it into two main components: the optimisation process and the energy system representation.

4.2.1.1 Optimisation process

The IESA-Opt model provides a cost-optimal system configuration and optimal technology usage for the energy-system transition of the Netherlands. As indicated in Figure 15, six input elements are required: the demands of the various activities based on macroeconomic projections, such as the number of houses or tons of steel required; the expected costs and operational parameters of the technologies that can meet the demand of the various activities; the technology and resource potentials; the price forecasts for the primary energy resources fueling all the energy transformation activities; the policy landscape assumed for the energy system comprising technology restrictions and emission reduction targets; and the European landscape, including the ETS carbon price and installed capacities of the generators in the 20 European Union (EU) nodes (excluding the Netherlands).

In addition, Figure 15 shows that, subsequent to the execution of the scenario run, the model provides direct results, such as the objective function value (i.e. total costs of the decisions of the entire system), the technological stocks (installed capacities) for the entire multi-year transition period; the investments[24], retrofitting, and premature decommissioning required to achieve such an optimal configuration; the (hourly) use of the technologies present in the system and their flexible operation deviations; the energy prices resulting from the endogenous energy transformation (e.g. electricity and hydrogen production); and the CO_2 shadow price resulting from imposing the emission cap. However, from these direct results, several other results can be obtained in a post-processing phase. The latter makes IESA-Opt ideal for describing various characteristics of the optimal energy transition, such as energy balances, renewable energy use, system and sectoral costs and emissions, levelized costs of electricity (LCOEs) of the technologies (after operation), visualisations of the hourly power dispatch, imports and exports of various energy carriers, curtailment of intermittent renewable-energy sources, level of electrification, and electricity profiles after flexibility is applied. It is important to highlight that the ability to simultaneously account for intra-year behaviour (i.e. hourly and daily dynamics) and multi-year capacity planning under perfect foresight for all the interlinked sectors of the energy system makes IESA-Opt a state-of-the-art tool for analysing the real costs of adopting VRES to achieve system decarbonisation.

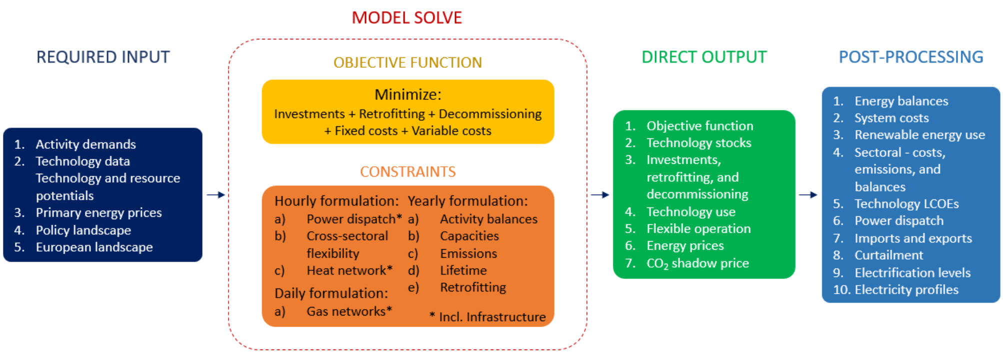

Figure 15, Methodological elements in the IESA-Opt framework.

In order to realise these results, IESA-Opt has being designed as a LP formulation that minimises the cost of investments, retrofitting, decommissioning, and operation. Its detailed formulation is presented in Appendix C. However, we present a conceptual description of the constraints used in the model. The optimisation problem is subject to a set of constraints used to describe the feasible transition and operation ranges of all the

[24] Investments are represented in the objective function while taking into consideration both the discount rate and economic lifetime merged into an annuity factor used to annualise the investments for each period.

technologies. We separated the constraints into three main categories based on their temporal resolution: yearly, daily, and hourly.

The yearly constraints comprise five constraint clusters with the following objectives: 1) to ensure that all driver activities (exogenous demand) are satisfied and all the endogenous energy activities are balanced; 2) to ensure that the use of technologies does not exceed the capacity and national potentials; 3) to impose the maximum lifetime of technologies; 4) to indicate which technologies might be transformed into another new technology (retrofitting); and 4) to enforce the GHG reduction target[25].

The daily constraints are focused on the feasibility of operation of the gaseous pipelines, namely, all the operating pressures of natural gas and hydrogen networks, as well as the transport of captured CO_2 (CCUS network). A daily balance is sufficient to capture the dynamics of gaseous networks, mainly owing to the buffer effect (line pack) of networks (where the hourly balance is not zero) [139]. The objective of using the daily resolution is to address seasonality, buffer opportunities, and infrastructure costs. To achieve this, two main constraints are implemented: the first one enforces a strict daily balance in the gaseous networks, which means that energy inputs and outputs must match daily, and the second one sets a cap for the daily transit of energy in a network in line with the available infrastructure. With this representation, the model dispatches national wells and imports, manages the daily operation of the buffers (e.g. gas storage chambers), and describes other generation processes with particular sectoral dynamics, such as fermentation, (bio)gasification, and electrolysers (which are also ruled by hourly constraints). In addition to the dispatch, in this formulation, the costs of required network expansions (e.g. investments in grid developments to transport hydrogen or captured CO_2) are taken into consideration.

The last category, corresponding to the hourly constraints, presents the heaviest mathematical burden for the optimisation problem and comprises the optimal dispatch for the power system. Modelling the power dispatch within ESMs demands that choices be made to avoid enormous computational requirements. Poncelet et al. [111] demonstrated that poor temporal resolution negatively affects the reliability of analyses with a moderate or high presence of VRES and recommended the use of hourly resolution

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[25] It is important to mention that approximately 85% of the emissions considered within the 2017 national inventory of the Netherlands [159] is accounted for by the activities included in the energy-system framework, and for the remaining 15% (primarily agricultural activities), a less-detailed approach is used. Here, the emissions resulting from activities such as enteric fermentation, manure management, and the use of fertilisers and refrigeration fluids are input into the model as driving activities, and their potential reductions and costs are addressed via marginal abatement cost curves (extracted from the IMAGE model database [110]). A complete description of the methodology is provided in Appendix D.

as a priority. They also concluded that the adoption of a sequential description of the power dispatch maintains the chronological order in the variability of the events, which is crucial for short- and long-term storage technologies. The same study highlighted the importance of unit commitment, which is used to describe start-up and shutdown times as well as minimum downtimes. This type of description of the power system requires the use of integer variables, which would turn the problem formulation into a mixed integer program (MIP). However, in the same study, it was stated that unit commitment loses relevance after a certain level of VRES penetration, owing to the presence of fewer thermal units in the system. This observation is further reinforced by another study, which states that MIP unit commitment performs better in studies with a low presence of VRES, but for high levels of VRES, an LP approach suffices for providing reliable results [101]. Similarly, there is plenty of evidence that an increase in the geographical scope of the model to take into consideration European cross-border interactions has a significant impact on the outcome reliability of the models [85]. Based on this, an LP model is proposed in this chapter, and an hourly resolution is adopted with the sequential power dispatch of the entire interconnected European electricity network, in addition to different voltage levels for the Netherlands and 20 EU interconnected nodes.

In a manner similar to the gaseous networks, this formulation accounts for the required investments in infrastructure expansions to transport and transform electricity among the three low-, mid-, and high-voltage lines considered. It also accounts for the investments required to increase the interconnectivity of the Netherlands with offshore windfarms and the surrounding countries. These infrastructure descriptions are presented with an hourly resolution for electricity.[26]

[26] Analogous to the case of electricity, the district heating network is also described at an hourly scale to represent the dispatch, storage, infrastructure capacities, and infrastructure expansions.

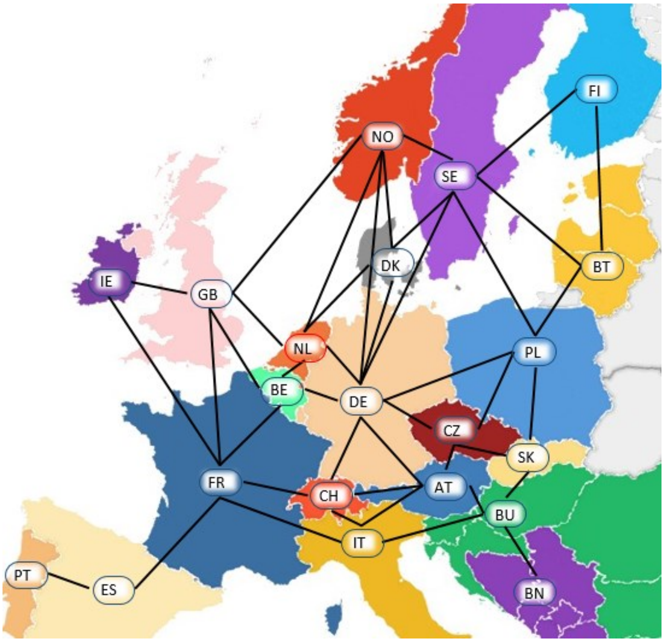

Figure 16, Nodal representation of the European power system considered in IESA-Opt.

The cross-sectoral flexibility is also described with an hourly resolution and is tailored to describe three types of modelled flexibility archetypes: combined heat and power (CHP), demand shedding, and conservational flexibility (which includes load shifting, storage, passive storage, smart charging, and vehicle-to-grid behaviours). CHPs provide flexibility in two dimensions: 1) by modifying their fuel input, and 2) by changing their heat-to-power ratio within a possible deviation range from a reference operation profile [136]. Demand shedding curtails the demand for electricity from a reference operation profile. This form of flexibility allows the system to overinvest in capacity [126] to allow a decrease in operation for hours when electricity is scarce and prices are high [125]. This flexibility form can be applied to various processes such as the production of heat [119], hydrogen [120], methanol [121], methane [122], hydrocarbons [152], chlorine [123], ammonia[124], and other chemicals [125]. In the case of load shifting, the system does not curtail but reallocates the energy demand by increasing and decreasing it at different hours (always within a feasible operating range). This conservational flexibility is modelled using three constraints: the balancing constraint, where the increases in energy demand over a certain time period must be equal to the decreases in electricity demand in another time period (plus the generated efficiency losses) inside a feasible rescheduling window; the capacity constraint, which states the upward and downward limits between which rescheduling can occur; and the saturation constraint, which states how much energy can be rescheduled inside a feasible rescheduling window. All demand responses [127], storage [153], passive storage [129], smart charging, and vehicle-to-grid transactions [131] fall within this flexibility archetype and are characterised by their own specific balancing, capacity, and saturation constraints.

4.2.1.2 Energy system representation

For each type of energy-system modelling, it is important to know what is included within the boundaries of the energy system under consideration. In IESA-Opt, the energy system is defined by activities and technologies, where the former refers to products and drivers in the economy and the latter refers to the different paths in which the model satisfies those activities (analogous to the commodities and processes nomenclature in TIMES [108]). Appendix C presents a complete list of activities and technologies of the system.

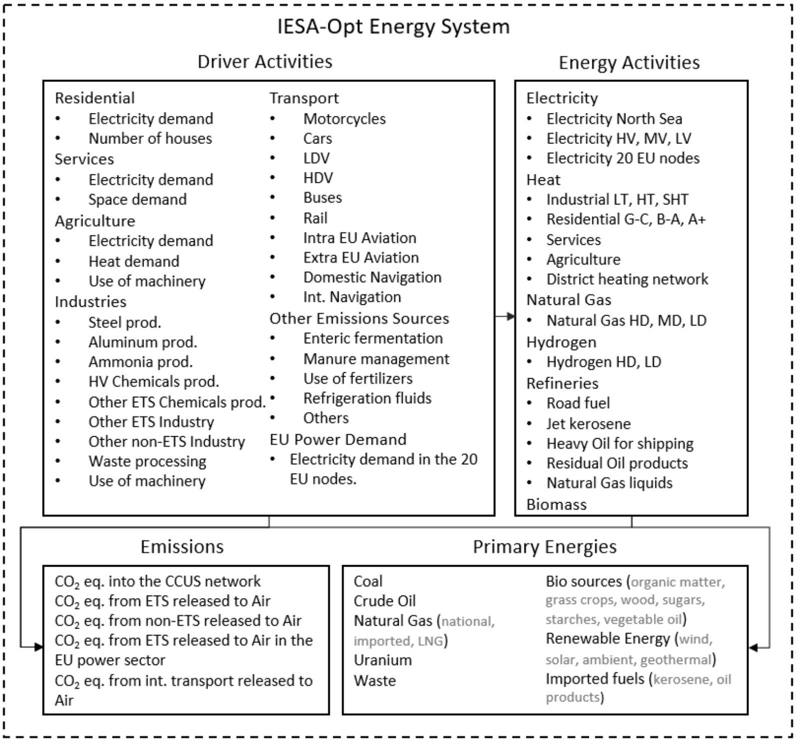

Figure 17, Energy system representation of activities considered within the IESA-Opt framework.

Conceptually, there are four types of activities: driver activities, energy activities, primary energies, and emissions. Figure 17 presents the specific activities that can be included within each type. Driver activities (final activities) comprise those corresponding to the five main sectors of the energy system (residential, services, agriculture, industry, and transport) along with the emission sources that are not fully contained in the energy system and the electricity demand of the 20 interconnected EU countries. Their volumes (demands) are fed into the model exogenously according to macroeconomic drivers, such that the model can decide which technologies will be used to satisfy them. The use of these technologies determines the energy requirements (both primary and processed energy) and the directly emitted CO_2 equivalents. The processed energy demand resulting from the use of technologies satisfying the final activities must then be met by the supply of energy from the energy conversion sectors (energy activities), such as electricity generation and oil refining. Here, the model decides which technologies to invest in and use optimally in order to satisfy the endogenous demand of energy at a lower social cost, thus resulting in primary energy requirements and related GHG emissions.

This energy system representation, wherein the non-energy-related emissions are included by means of their marginal abatement cost curves (MACCs) [110], allows for a complete description of the energy-related costs and a complete account of the emissions considered within the national targets.

4.2.2. **Scenario definition**

As mentioned in the previous section, the definition of a reference scenario in IESA-Opt includes six definitions of the required inputs, namely, the projected demand of driving activities, cost of input resources (primary energy costs), potential for decarbonisation technologies, policy regulations assumed for the transition, projected costs and operational parameters of the technologies, and assumed EU power system capacities (Figure 18). In this section, the sources and definitions of the storylines for each of these definitions are outlined briefly, while the explicit parameters used for this case study are reported in Appendix D.

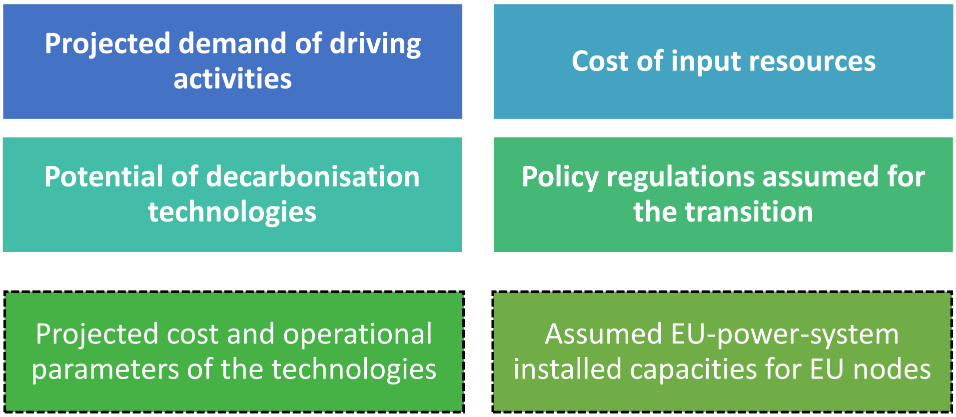

Figure 18, Six required scenario definitions of IESA-Opt

For the first two types of activities, the projected demand of the driver activities and part of the resources' costs are extracted from JRC's POTEnCIA Central Scenario for the Netherlands [154], which was adapted in line with the GDP growth rates presented in the 2018 Ageing Report [155]. These projections imply a business-as-usual economic development, which falls within the narrative of the second shared socioeconomic pathway[27] (SSP2) [156]. Biomass costs were extracted from the reference case of the ENSPRESO database [157] as well as the majority of the considered potential renewable technologies in the Netherlands, which also corresponds to their reference estimations (moderate potential).

The environmental policy landscape of the Netherlands is presented by the Dutch government in the National Energy and Climate Plan [158] and includes climate policy targets of 49% and 95% emission reductions for 2030 and 2050, respectively, compared with the 1990 levels[28]. This target includes emissions from energy use, industrial processes, agriculture, and waste management, which are required to completely account for the target in line with the data from the National Inventory on GHG emissions of the Netherlands [159].

This reference scenario for the Netherlands imposes two key constraints on nuclear and coal power generation. Although there is no explicit Dutch policy banning the use of nuclear power, there seem to be no plans in the short- or mid-term to further adopt it, and it will most probably disappear from the mix after 2033 [160]. For this reason and the apparent low social acceptance of nuclear power in the Netherlands, this reference scenario forbids the use of nuclear technologies after 2035. In addition, the Dutch Climate Agreement of 2019 prohibits the use of coal for power generation after 2030, although it is not yet clear if it will be allowed in combination with CCUS [161]. Therefore, coal power plants will not be allowed to run after 2030, but coal with CCUS is allowed in this scenario. In addition to these two constraints, the scenario considers no imposed social or policy constraints for the adoption of technologies, and thus, the model scenario output reflects a cost-optimal configuration based merely on technical restrictions.

Next, the technology-specific parameter set consists of the activity inflows and outflows for each technology (i.e. energy or commodity balance) and the cost profiles of the technologies (i.e. investment, and fixed and variable operational costs). Therefore, part of the scenario description requires projections of the cost and efficiency development of maturing technologies. This reference scenario comprises the gathered data from various central scenario descriptions of various sources. Most of the technologies described in IESA-Opt are based on the reference scenario of the ENSYSI model [162] wherein novel

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[27] The five SSP scenarios used to produce IPCC assessment reports explore the way the world may change over this century under different storyline assumptions. The SSP2 storyline explores a future wherein moderate efforts are taken to mitigate climate change, primarily based on the adoption of basic climate policies and continuous uneven economic development among countries.

[28] Emissions in the Netherlands accounted for 222 Mton CO_2 eq. in 1990 excluding land use, land-use change, and forestry [159], which translates to a cap of 108 and 11 Mton CO_2 eq. for 2030 and 2050, respectively.

low-carbon technologies experience a maximum learning rate of 20%. The model also bases technology data projections of the transport sector on those from the POTEnCIA Central Scenario [154]. Moreover, the reference scenario uses data projections from the available technology sheets of the Netherlands Organisation for Applied Scientific Research (TNO) [163] for technologies such as power-to-liquid alternatives, electrolysers, and direct-air-capture units. The complete technology data assumptions for this scenario as well as the link to the sources may be referred to on the web portal of the model [151].

As IESA-Opt dispatches electricity for the whole of Europe, the climate targets of EU-member-state power systems influence the mix of generation assets of interconnected nodes (which is a key indirect input element of the scenario definition). Member states must adhere to the EU targets, but additional (voluntary) national policy measures and contributions may vary. Such a variety of responses could strongly influence the outcome of the model, as the level of discrepancy in national policies may raise price differences, thus resulting in highly imbalanced import and export flows. To address this issue, the reference scenario considers EU generation assets from the mid-term adequacy forecast 2016 and the Sustainable Transition scenario runs until 2035 by the European Network of Transmission System Operators for Electricity [164] and is then complemented with updated data from the National Trends TYNDP scenario 2020 for the year 2040 [165]. Based on this configuration, we run a highly decarbonised capacity expansion plan for all European countries for the years 2040, 2045, and 2050 to ensure that the power generation assets of the Netherlands are aligned with those of other European countries. In this manner, we avoid highly unbalanced import and export situations due to modelling discrepancies for the years 2045 and 2050. The resulting European power system configuration used for this scenario is presented in Appendix G.

Sections 3 and 4 present the modelling results of the aforementioned case study. Section 3 presents the results of a single run using the model to explore the scenario described above. Section 4 presents deviations from the reference scenario in the form of sensitivity analyses to explore the following topics: 1) climate policy targets and the role of biomass and CCUS in achieving various objective levels; 2) the use of oil-based products (OBPs) neglected by current climate policy and how climate policy could be expanded to include them; 3) price and availability uncertainty of biomass in the system outcomes; and 4) uncertainty in demand volumes (activity levels) of the driver sectors of the economy.

4.3. Insights obtained from the reference scenario

In this section, we present the results of the reference scenario described in section 4.2.2. The results are split into seven subsections, each addressing one particularity of the energy transition or an advanced capability of the model. The first three subsections are focused on the energy mix, emissions, and transition costs. Subsection four describes the generalities of the resulting system configurations. The next subsection illustrates how the model represents the operation of the gas networks. Subsection six presents the particularities of the power sector in the resulting transition. Finally, the last subsection is focused on the role of cross-sectoral flexibility.

4.3.1. **Energy Mix**

A crucial output element delivered by ESMs is the energy mix. Figure 19 presents the energy mix for the Netherlands resulting from the optimisation of the reference scenario. This graph shows that the main transformation is, as expected, the substitution of fossil fuels with renewable energy sources. It should be noted that there is a significant reduction in the use of oil, which is mainly triggered by the substitution of fossil transport alternatives. It is important to mention that the use of coal is almost negligible in 2050, and it only remains in use in the steel sector in the form of a small amount of blast-furnace capacity with CCUS. In contrast, natural gas still comprises an important share of the mix, mainly because of its adoption as a shipping fuel and the emission window for non-ETS activities opened by the negative emissions of the biomass and CCUS coupling.

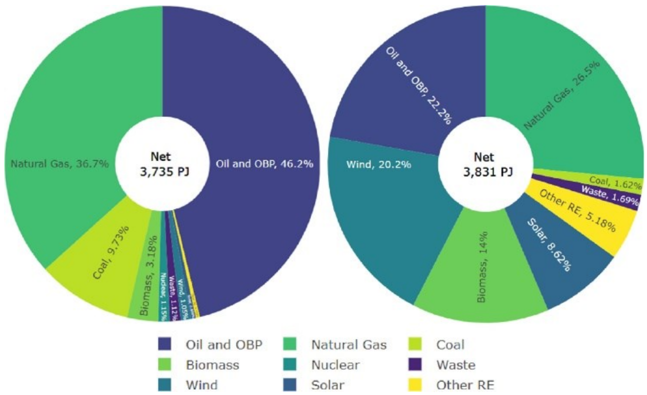

Figure 19, Netherlands' primary energy mix in IESA-Opt (including international transport). Left: 2020. Right: 2050.

Furthermore, in addition to the considerable share of natural gas, the presence of oil and OBPs in the 2050 primary energy mix shows the way in which the current climate policies are insufficient for avoiding the use of fossil fuels. As shown in Figure 20, most of the remaining uses of OBPs are outside the scope of the currently adopted climate policies in the Netherlands. This figure shows an increased use of kerosene for aviation and OBPs for industrial feedstock, while refineries are still being fuelled with oil (although they adopt CCUS). These three activities are neglected by the current adopted climate policy due to the following reasons: 1) there is no emission reduction target in effect for international transport emissions in the Netherlands; 2) OBPs used for industrial feedstock flows are embedded in products and do not result in GHG emissions until they are incinerated as waste; and 3) refineries produce a significant amount of fuels and OBPs that is exported and does not result in GHG emissions in the Netherlands. Climate policies focused on these factors are necessary for decreasing the amount of fossil fuels used in the 2050 energy system.

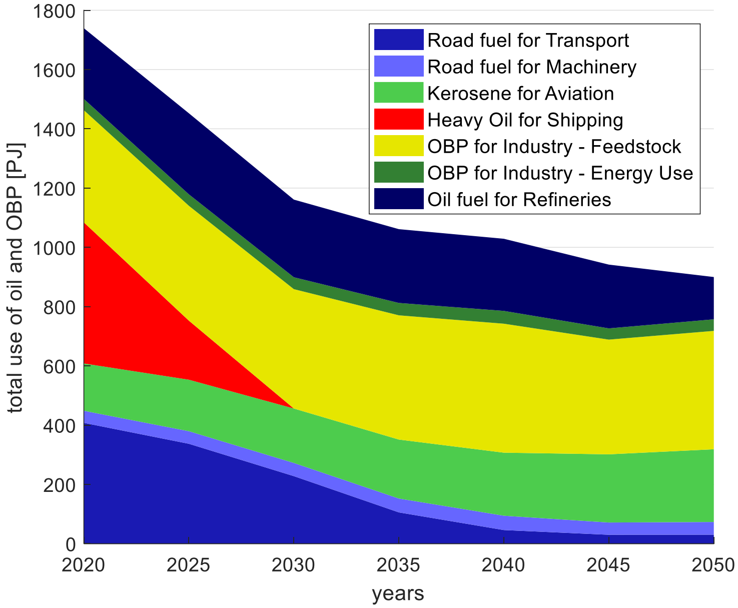

Figure 20, Long-term evolution of the use of oil and OBPs by activity[29].

The adoption of renewable energies during the transition is reported in Figure 21, where it can be observed that their use in 2050 is 10 times more than that in 2020. The most pronounced increase is due to the adoption of wind energy (i.e. wind turbines), which accounts for over 40% of all renewables in 2050. Biomass plays a crucial role in the final years when it is being supplied for the production of olefins to produce industrial feedstock in the chemical sector, which, next to biofuels and other biomass sources, account for over 500 PJ, that is, approximately a quarter of the share of renewables. This role of biomass is largely due to the possibility of importing biofuels (330 PJ) and wood (320 PJ)[30], the values of which are assumed to be intermediate values provided by the two TNO scenarios for a climate neutral energy system for the Netherlands [166]. The usage of

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[29] The reported oil fuel for refineries represents conversion losses. Also, only the net oil and OBPs used in the Netherlands are reported in the graph; hence, exported road fuels and OBPs are not included.

[30] It is well understood that biomass for energy purpose is strongly constrained by the water-food-land nexus, making its future availability a critical uncertainty for the transition. Such nexus was not considered for this study when selecting these potentials. However, the figures are in line with the levels of bio-energy production potentials for 2050 according with the IMAGE model, which estimates 8–15% of the total final consumption [305].

these two energy sources is followed by that of solar energy (i.e. photovoltaics), which comprises approximately 15% of the share of renewables. It is also possible to observe a pronounced role of geothermal and ambient energy used for heating purposes (shown in the graph under other renewables). It is important to mention that the potentials assumed for the adoption of renewable energies are based on sources (Appendix D) that account for the land use of the corresponding technologies (e.g. wind turbines, photovoltaic cells, and space for biomass farming).

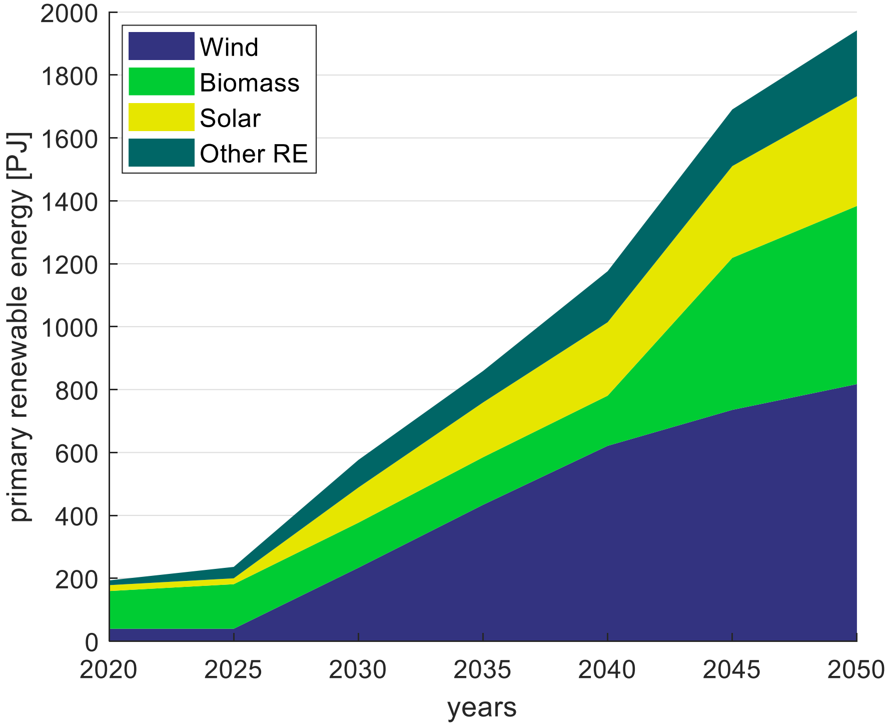

Figure 21, Long-term evolution of renewable energy production by source

To better understand how energy is being used, Table 13 lists the energy flows according to the standard indicators commonly used by CBS in the national energy balance [167]. This table shows a decrease in the final energy usage for the first part of the transition, which is due to the early retrofitting of all the energy-efficient options (it is important to mention that it is an optimisation model, and thus, the obtained results are not predictions). It is also interesting to note that the sudden decrease in energy transformation in 2030 is mainly driven by the decommissioning of coal generators and an increase in the use of renewable sources in accordance with the 2030 target. Subsequently, the energy transformations increase again as a consequence of the adoption of power generation from gas and owing to the hydrogen production from electrolysis in 2050. Finally, the electrification of activities is evident, as the amount of final electricity used in 2050 almost doubles that in 2020, while the system also uses 9% less final energy.

Energy Account	Units	2020	2025	2030	2035	2040	2045	2050
Net primary	PJ	3,735	3,666	3,307	3,391	3,459	3,726	3,831
Net energy transformations	PJ	680	817	467	529	539	660	656
Total final including international transport	PJ	3,168	2,959	2,955	2,981	3,037	3,178	3,291
International transport	PJ	621	666	688	724	758	796	831
Total final excluding international transport	PJ	2,547	2,293	2,266	2,257	2,280	2,382	2,460
Feedstock	PJ	482	498	518	534	540	532	538
Final energy use	PJ	2,065	1,796	1,748	1,723	1,740	1,850	1,922
Losses in final energy use	PJ	123	105	88	99	74	82	91
Final electricity	PJ	393	404	453	529	629	669	723
Total electricity	PJ	434	443	523	613	783	885	1,103

Table 13, Evolution of the Netherlands' primary and final energy account in IESA-Opt.

The sectoral disaggregation of the resulting 2050 final energy consumption is presented in Table 14. Here, we observe that the final energy consumption of all the sectors tends to decrease except in the case of the industrial sector, which, despite efficiency improvements, uses more energy in 2050 owing to an increase in activity volumes. The most evident difference is the significant decrease in transport energy use despite the higher activity volume. This is explained by the electrification of the transport fleet, which reduces conversion losses typically inherent to burning fuels in internal combustion engines. Finally, systemic electrification is completed by the partial electrification of utilities in industry and the adoption of more electric-based machinery in agriculture.

Sector	Total [%]		Total [PJ]		Heat [PJ]		Electricity [PJ]		Fuels [PJ]		Feedstock [PJ]	
	2020	2050	2020	2050	2020	2050	2020	2050	2020	2050	2020	2050
Residential	16%	13%	395	297	311	205	85	92	0	0	0	0
Services	11%	9%	280	202	150	67	130	135	0	0	0	0
Agriculture	6%	8%	155	185	96	111	37	53	22	21	0	0
Transport	17%	12%	433	276	0	0	8	228	425	48	0	0
Industry	49%	60%	1232	1415	362	297	142	230	245	349	482	539
Total Final	100%	100%	2495	2376	919	681	402	738	692	418	482	539

Table 14, Sectoral composition of final energy in 2050.

4.3.2. **Emission pathway**

The climate policy of 45% and 95% emissions reductions for 2030 and 2050, respectively, indicates a maximum of 113 and 11 Mton of CO_2 eq. per year, respectively. Based on this, IESA-Opt provides the optimal emission abatement pathway in the ETS and non-ETS sectors for this transition, as shown in Figure 22. Here, it is shown that the ETS sectors undertake the greatest abatement responsibility as they present a pronounced and accelerated reduction path, while even realising negative emissions in 2050. Interestingly, in the years 2040 and 2045, the system decarbonisation exceeds the 2030 emissions reduction target in a cost-effective manner, as indicated by the null-emission shadow price. Subsequently, when the second reduction target is introduced in 2050, the emission shadow price increased to almost 560 €/ton of CO_2. This is almost four times higher than the 2030 shadow price, which indicates that, if the targets are adhered to seriously, the transformation required for the decade after 2040 will impact the system more aggressively than the impact we are experiencing in this decade. However, further research and development efforts can aid in mitigating the extra costs, as the technological learning considered for this scenario is based on conservative projections. In addition, it is worth mentioning that the model does not yet include all of the potentially available decarbonisation options in the industry (as we do not explicitly model furnaces, materials recycling, or highly innovative processes with low readiness indexes), and that new innovative technologies may mature in time to assist the transformation.

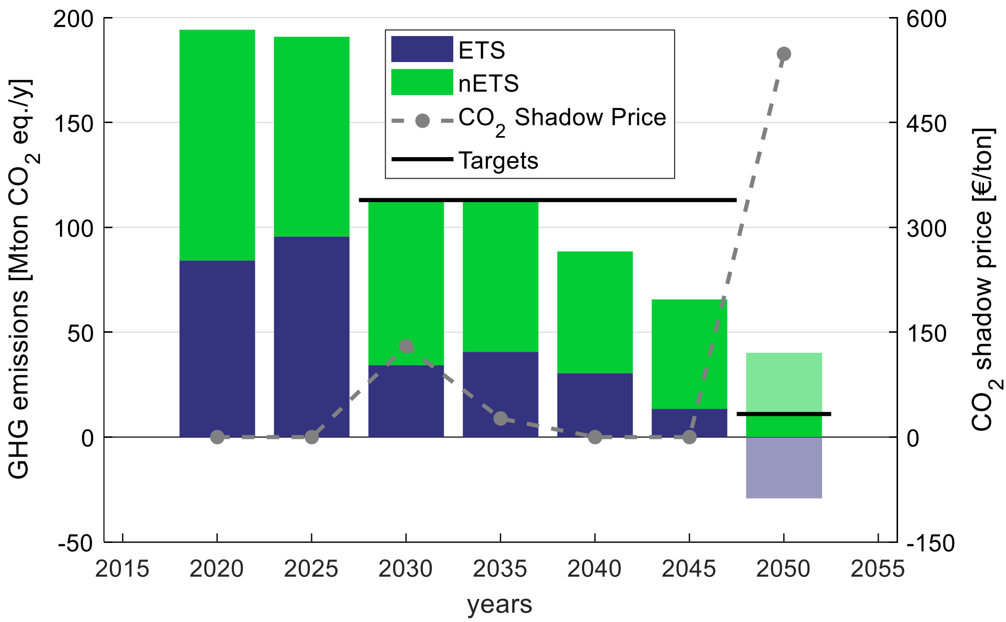

Figure 22, Long-term evolution of CO_2 emission and price in ETS and non-ETS sectors

The current climate policy focusing on decarbonisation targets only for the years 2030 and 2050 may result in behaviours such as the shadow prices of the emission reduction constraint, as shown in Figure 22. Hence, in Figure 23, we compare the current climate policy with two alternative decarbonisation paths in which a) only the 95% emission reduction target in 2050 is considered and b) a linear decrease from 49% reduction in

2030 to 95% reduction in 2050 is followed. This figure shows that even when the target is only imposed in 2050, the system already reduces over 70% of the emissions by 2045. Interestingly, the objective functions of the three presented paths do not differ significantly: for the 2050 target, the value is B€ 314.4; for the 2030 and 2050 targets, the value is B€ 314.8; and for the linear progression, the value is B€ 315.3. However, the system configuration also varies among the three cases, especially in the power sector and particularly in the imports and exports of electricity (although the Netherlands becomes a net exporter in these three cases). The most-constrained path (linear progression) presents higher imports and slightly lower exports of electricity for all the years, while the least-constrained path (only a 2050 target) presents the lowest imports and highest exports of electricity. This is owing to the extra room for emissions from thermal generation units, which can provide electricity for national and external demand. Furthermore, the average emissions for the period increased from 111 Mton of CO_2/year with the current climate policy of 124 Mton of CO_2/year when the target is only imposed for the year 2050, and decreased to 99 Mton of CO_2/year when the targets are decreased linearly. This observation results in the requirement fora direct recommendation to policy makers to include more intermediate targets for the energy transition, as they could reduce the cumulative emissions by more than 10% while maintaining the transition cost increase at less than 1%.

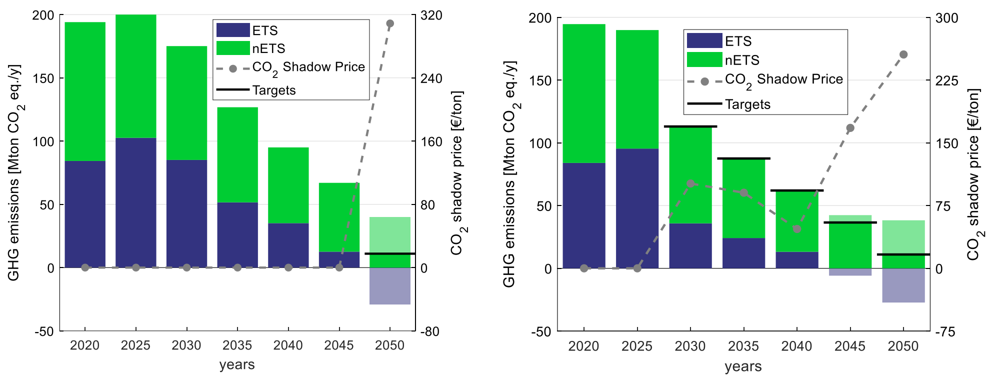

Figure 23, Alternative climate policy paths for the emission reduction targets. Left: only with a 95% emission reduction target in 2050. Right: linear reduction of the target from 49% in 2030 to 95% in 2050.

4.3.3. **System costs**

The resulting transition path is characterised by a progressive increase in system costs until 2050, with a slight peak in 2045, as illustrated in Figure 24. This general upward trend is driven by the climate policy, along with the assumed economic growth and increases in the prices of fossil fuels and biomass. The 2045 peak can be attributed to the effect of the anticipation of the 2050 emission target on the power sector investments and is partially caused by the impact of (exogenous) technological learning. It is important to mention that the anticipation of the target in the power sector results in higher electricity exports in 2045 as both flexible thermal generation and excess intermittent generation can be placed outside the Netherlands easily, as required, while the 2050 target makes this "symbiosis" between thermal and intermittent generators less frequent. Therefore, in 2050, there is a considerable reduction in the electricity export flows as the power system can no longer use CO_2-emitting thermal units freely to provide flexibility to the national (and part of the European) power system. Finally, a switch from variable to capital costs is also observed, which is mainly driven by the adoption of wind and solar energy sources that lack a fuel-cost component. It is important to mention that variable costs, which include both variable operational costs and fuel costs in this graph, decrease both in share and absolute terms, despite the assumed growth in fuel prices (fossil and biomass).

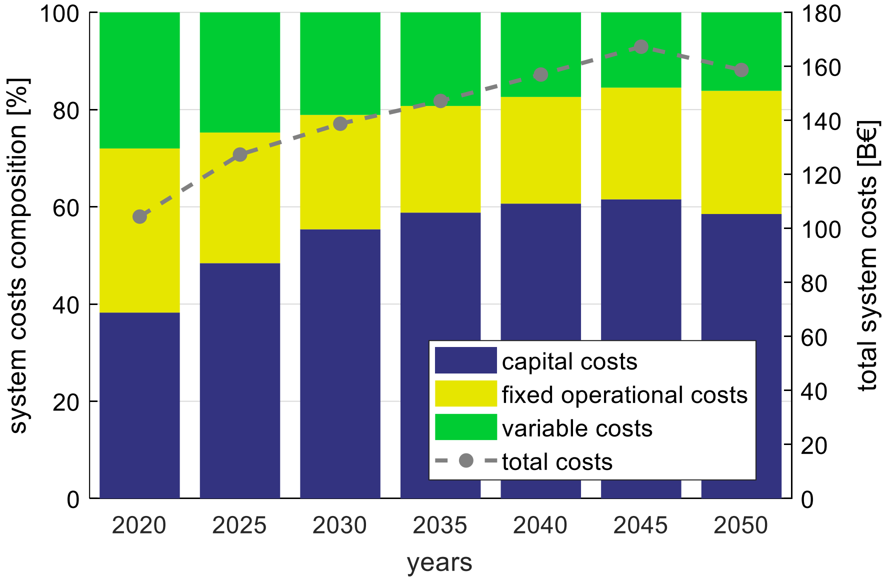

Figure 24, Long-term system cost evolution.

To better understand the cost composition of the system, it is worth analysing the sectoral costs while bearing in mind the cost definitions presented in Table 15. The four cost perspectives included in the IESA-Opt model are as follows: 1) the objective function that considers the problem perspectives on the costs of decisions; 2) the energy prices representing the market perspective of the costs of commodities; 3) system costs, which describe the cost impact of the energy transition at a national scale; and 4) sectoral costs, which address the users' perspectives on cost for each sector considered in the model. These cost definitions aid in understanding the difference between the system costs presented in Figure 24 and Figure 25. In the sectoral costs definition presented in Figure 12, if a sector uses any form of processed energy (e.g. electricity), it must pay the energy price at the time of use (e.g. producing electricity at a certain hour costs the system less than what the final users pay).[31]

Cost Perspective	Definition
Objective function (Problem perspective)	This cost perspective directly reflects the planning and operational decisions in the mathematical problem. Hence, it reflects annualised (and discounted) investments for new and retrofitted technologies, fixed costs of having a technology in the system, capital recovery (if any) of premature decommissioning, and variable operational costs (fuel consumption and other variable costs).
Energy prices (Market perspective)	The energy prices are reflected by the dual variables of the energy balance constraints. Therefore, they reflect the market value of a commodity in the model and are used to account for the energy costs of imports and exports as well as for sectoral costs analyses.
System costs (National perspective)	System costs are obtained after post-processing planning and operational decisions as considered in the objective function. Here, the distinction between the national system and "problem appendices" is made explicit (EU power system, refineries exports, and gas exports). The post-processing accounts for the cross-border trading component of electricity, gas, and OBPs. It should be noted that this form of reporting keeps track of the capital cost component of the planning decisions based on the costs of the decision period and the economic lifetime of the decision.
Sectoral costs (Users' perspective)	Sectoral costs explicitly account for the fuel prices paid by each sector based on the market perspective of the energy costs. This means that the total sum of costs in all sectors will be higher than the system costs, as this definition accounts for the hidden added value of the energy prices. Furthermore, the trading component mentioned for the national system costs is allocated to each specific sector under this definition. Finally, the sectoral cost provides a further disaggregation, as the infrastructure costs are explicitly reported here (while they are regarded as capital and fixed operational costs from the national perspective), which is also the case for the emission ETS costs (which are regarded as variable costs in the system costs definition).

Table 15, Definitions of the different cost perspectives included in the IESA-Opt model.

[31] The electricity price resulting from shadow prices represents the generation cost of the marginal generator, and includes both the capital and operational cost components of the objective function (as done by other models such as EMMA [306]). However, it is important to mention that when computing shadow prices, it is also possible to fix the installed capacities to get only the operational component represented in the dual variable. The latter would reflect more closely what happens in the Netherlands' energy-only market approach with an imperfect scarcity price, but it does not guarantee that all the generators can recover the investments (this is typically known as the missing money problem). There are different market proposals to address the issue [306], but further elaboration would fall outside of the scope of this study. It is also important to mention that a value of lost load (VOLL) of 3,000 €/MWh (in line with the maximum bid allowed in the EPEX SPOT market) was used to facilitate feasibility, hence it also affect the shadow prices when dispatched.

This differentiation of the cost perspectives enables us to observe the different impacts of the transition in all four final sectors from the users' perspective, as shown in Figure 25. For instance, in the residential and services sectors, there is an immediate adoption of improved space insulation (from the cost optimal perspective), which drives a sudden increase in capital costs and a progressive decrease in fuel costs. In contrast, the agriculture sector does not exhibit an increase in the capital cost of energy until late in the transition, while the fuel cost component steadily decreases in the meantime. The transport sector trend shows a progressive increase in the capital intensity until it peaks in 2035, while the fuel cost component remains approximately constant. The latter is a notable result for the sector, as it implies that the decrease in fuel costs brought on by the electric fleet aids in mitigating the increase in fuel costs of the other transport activities. Finally, the industrial sector is affected by an increase in capital, fuel, and emission costs, and it also shows a decrease in costs from 2045 to 2050, which is apparent in the total system cost figure. This occurs because many industrial activities wait until cheaper technology is available in 2050, which results from the steep technological learning in the sector (exogenous).

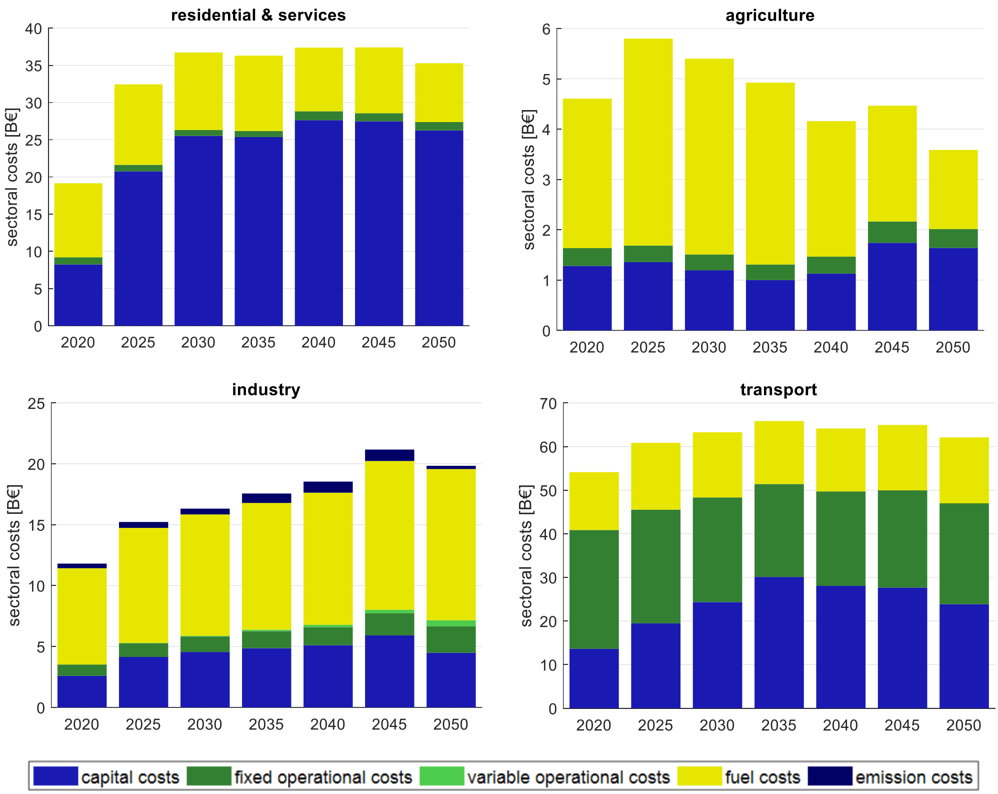

Figure 25, Sectoral cost disaggregation. Top left: Residential and services sector. Top right: Agriculture sector. Bottom left: Industry sector. Bottom right: Transport sector.

The electricity sector costs, as shown in Figure 26, are also interesting to explore, as this sector hides many elements that influence the evolution of the total system costs. In addition to the substantial increase in power sector costs, this graph evidences the close relationship between electricity trading and the emission reduction target from the optimality perspective. When climate policy is adopted in 2030 and 2050, it directly affects the freedom of the system to use fossil-based generation, which is reflected in an increase in import costs and a significant decrease in revenues from exports. Furthermore, the assumed climate policy results in a complete decommissioning of coal power plants in 2030, which are substituted by over 30 GW of VRES capacity, which drives the reduction of fuel costs. Subsequently, the VRES adoption continues as the installed capacity is increased to over 170 GW, which is supplemented by a steady increase in cross-sectoral flexibility, storage (compressed-air energy storage (CAES)), and the use of available thermal capacity (namely, combined cycle gas turbines), which results in a significant increase in exports. Finally, the accentuated electrification and the increasing shares of VRES drive a progressive expansion of the electricity network, which contributes to the reported increase in system costs.

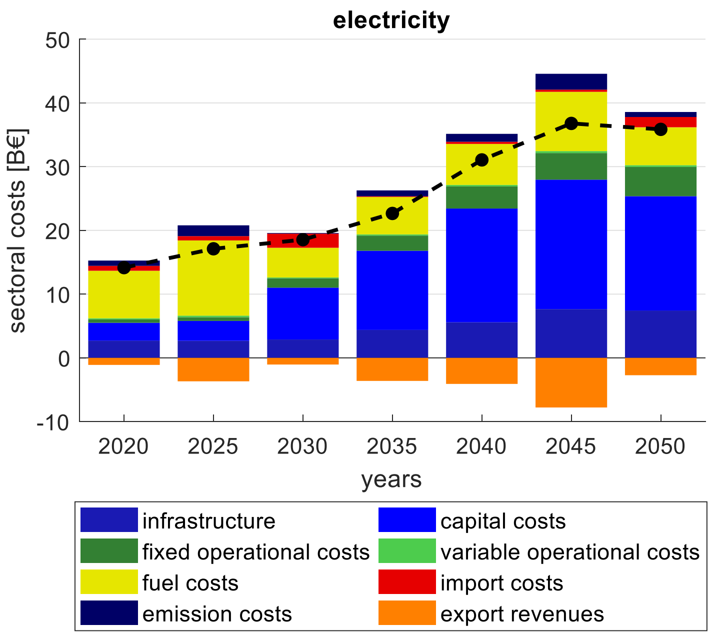

Figure 26, Cost disaggregation for the electricity sector.

4.3.4. **System configuration**

All the outcomes of a scenario run are related to the technological configuration of the system. IESA-Opt can simultaneously determine the cost-optimal technological stock (and its usage) of various sectors for the considered transition period. Table 16 presents an overview of the use of all the technologies required for satisfying the main sectoral activities for the entire transition. This reported trend shows that the model choices switch toward greener alternatives.

For instance, the industrial sector starts adopting novel technologies such as electrolytic steel production [168] or solid state ammonia synthesis (SSAS) for ammonia production to reduce emissions by electrification. In addition, electrolysers are being adopted at both decentralised and centralised locations to produce hydrogen mainly for refineries. In addition to electrification, other decarbonisation paths can be observed in the industry sector, such as the use of biomass to produce olefins and the adoption of heat from biomass with CCUS to provide negative emissions. As a general observation, CCUS is widely adopted in the industrial sector owing to its high CO_2 storage capacity and the possibility of using it as a sink (e.g. the production of synthetic fuels from electricity and CO_2 in 2050).

Sector	Activity	Technology	Units	2020	2030	2040	2050
Industry	Steel production	Blast furnace	Mton	6.9	6.7	4.5	0.0
		Blast furnace with CCUS	Mton	0.0	0.0	0.0	4.5
		Hisarna	Mton	0.1	0.0	0.0	0.0
		Hisarna with CCUS	Mton	0.0	0.0	0.5	0.0
		ULCOWIN	Mton	0.0	0.0	1.9	2.8
	Ammonia production	Haber Bosch	Mton	2.8	0.8	0.0	0.0
		Haber Bosch improved	Mton	0.0	0.9	0.0	0.0
		Haber Bosch improved with CCUS	Mton	0.0	1.2	2.1	1.7
		Solid State Ammonia Synthesis (SSAS)	Mton	0.0	0.0	1.0	1.7
	Petrochemical transformation	Naphtha steam cracker	Mton	7.2	0.4	1.1	0.0
		Naphtha steam cracker improved	Mton	0.0	7.2	7.2	0.0
		Naphtha steam cracker improved with CCUS	Mton	0.0	0.0	0.0	7.4
		Olefins from biomass	Mton	0.0	0.1	0.0	1.3
	Industrial heat	Boiler gas	PJ	237.1	83.6	83.5	0.0
		Boiler coal	PJ	3.0	0.0	0.0	0.0
		Boiler coal with CCUS	PJ	0.0	0.0	17.3	0.0
		Boiler biomass	PJ	0.0	42.7	0.0	0.0
		Boiler biomass with CCUS	PJ	0.0	30.8	30.0	94.3
		CHP gas	PJ	58.0	0.2	0.3	0.0
		CHP biomass	PJ	0.8	9.9	0.3	0.1
		CHP biomass with CCUS	PJ	0.0	0.3	40.4	100.4
		Electric heat pump	PJ	0.0	50.6	50.6	50.6
		Geothermal heat pump	PJ	0.0	43.9	46.8	65.5
Transport	Motorcycles	Internal combustion engine (ICE) vehicle	Gvkm	4.8	5.7	4.1	0.3
		Electric vehicle	Gvkm	0.3	0.2	2.4	6.9

Sector	Activity	Technology	Units	2020	2030	2040	2050
	Cars	ICE vehicle	Gvkm	108.3	64.6	0.0	0.0
		PI Hybrid vehicle	Gvkm	1.1	0.3	0.0	0.0
		Electric vehicle	Gvkm	1.1	49.5	119.2	125.3
	LDV	ICE vehicle	Gvkm	20.9	13.8	0.0	0.0
		Electric vehicle	Gvkm	0.1	10.4	27.4	32.3
	HDV	ICE vehicle	Gvkm	7.4	6.5	0.6	0.0
		Electric vehicle	Gvkm	0.0	1.1	7.4	8.3
	Buses	ICE vehicle	Mvkm	298.2	28.1	0.0	0.0
		Natural gas vehicle	Mvkm	305.0	584.0	332.3	0.0
		PI Hybrid vehicle	Mvkm	2.4	1.2	0.0	0.0
		Electric vehicle	Mvkm	11.6	11.1	305.0	650.0
	International navigation	Heavy oil ship	Mvkm	110.0	0.0	0.0	0.0
		CNG ship	Mvkm	0.0	125.0	135.0	145.0
Residential	House insulation	Insulation level GFE	Mhouses	2.1	0.0	0.0	0.4
		Insulation level DC	Mhouses	3.0	0.0	0.0	0.1
		Insulation level B	Mhouses	1.9	0.0	0.0	0.0
		Insulation level A	Mhouses	0.9	0.3	0.2	0.0
		Insulation level A+	Mhouses	0.4	8.5	9.1	9.2
	Heating technology	Boiler gas	PJ	249.2	187.5	176.4	169.2
		Boiler gas with wood stove	PJ	49.0	1.4	0.0	0.0
		Boiler gas with solar heater	PJ	1.0	1.0	0.0	0.0
		District heating	PJ	0.0	0.3	3.5	15.0
		Hybrid heat pump	PJ	10.0	6.2	0.0	0.0
		Electric heat pump	PJ	1.5	5.7	20.8	20.8
Services	Space insulation	Insulation level GFE	Mm^2	190.0	0.0	0.0	0.0
		Insulation level DC	Mm^2	100.0	0.0	0.0	0.0
		Insulation level B	Mm^2	210.0	0.0	0.0	0.0
		Insulation level A	Mm^2	10.0	0.0	0.0	0.0
		Insulation level A+	Mm^2	5.0	540.0	555.0	560.0
	Heating technology	Boiler gas	PJ	127.8	27.8	0.0	0.0
		District heating	PJ	3.7	0.0	0.0	0.0
		Hybrid heat pump	PJ	10.0	5.0	26.0	26.0
		Electric heat pump	PJ	3.0	1.5	0.0	0.0
		CHP gas	PJ	6.0	36.9	43.5	40.5
Agriculture	Machinery	Fuel based	PJ	20.7	23.8	27.7	12.0
		Hybrid	PJ	2.1	1.5	0.0	18.2
	Heating technology	CHP gas	PJ	81.3	69.3	24.6	0.1
		Geothermal heat pump	PJ	5.6	22.4	72.2	100.0
		Shallow soil energy heat pump	PJ	0.3	0.3	0.0	1.5
		Boiler gas	PJ	8.2	8.8	9.2	9.6
Refineries	Oil refining	Deep cracking	PJ	554.0	1234.2	949.3	0.0
		Deep cracking with CCUS	PJ	0.0	0.0	210.2	1068.8
		Basic cracking	PJ	649.0	0.1	0.0	0.0
		Basic cracking with CCUS	PJ	0.0	150.2	0.0	0.0
		Koch refinery	PJ	18.0	0.0	0.0	0.0
		Koch refinery with CCUS	PJ	0.0	19.0	22.8	26.6
		Power to liquids	PJ	0.0	0.1	1.3	84.4
		Biorefineries	PJ	23.0	15.0	0.1	0.0
		Biorefineries with CCUS	PJ	0.0	0.0	25.0	25.0

Sector	Activity	Technology	Units	2020	2030	2040	2050
Heat Network	Heating technology	Boiler Gas	PJ	3.5	0.0	0.0	0.0
		Geothermal gas heat pump	PJ	0.0	0.1	3.0	14.7
		Hot water storage tank	PJ	0.2	0.3	1.9	7.0
Hydrogen	Hydrogen production	Alkaline electrolyser	PJ	0.0	0.0	0.8	78.0

Table 16, Evolution of the system configuration for different sectors.[32]

The transport sector also undergoes a complete transformation. The model run of the reference scenario results in the predominant presence of electric vehicles (EVs) as the cost-optimal configuration for the road subsector. Similarly, within the navigation subsector, heavy oil ships were substituted with compressed-natural-gas-engine (CNG-engine) ships. The rest of the transport sector remains largely unchanged, primarily because trains are already electric and because emissions from kerosene planes are not addressed by the existing climate policy.

For the residential and services sectors, the model determines the optimal path for retrofitting all the spaces to the maximum level of insulation as quickly as possible. It then uses boilers, district heating, and electric heat pumps to meet the reduced residential heat needs and gas CHPs and hybrid heat pumps to supply heat for service spaces. A system running on geothermal energy and hot water storage tanks is adopted by the scarcely used district heating network to provide flexibility to the supply.

Similarly, the agriculture sector uses geothermal energy to satisfy its heat demand. However, this outcome would be different if spatially sensitive data were used to only allow certain regions to adopt geothermal energy according to its availability.

It is also important to highlight the role that retrofitting plays in determining the cost-optimal system configuration, as it provides a significant amount of flexibility for investments. The obtained system configuration perfectly illustrates the advantage of this modelling capability, especially in terms of efficiency improvements and the adoption of CCUS modules, which are adopted by the system progressively as the system needs them to meet the decarbonisation targets.

4.3.5. **Temporal dynamics of gas networks**

In contrast to the electricity network, the IESA-Opt balances the gaseous networks in daily time frames [139]. This modelling choice provides the advantage of observing seasonal

[32] To synthesise information, some years and some technologies are omitted from the table. Furthermore, some technologies were grouped together, and some granularity is thus lost in the report. A table with a complete list of technologies is provided on the web portal of the model [151].

variations while maintaining low computational requirements. For instance, the seasonal variation in the natural gas network is presented in Figure 27. The medium density (MD) network appears similar in 2020 and 2050 because MD network is connected to the built environment heating, and we use the same reference profile for built environment technologies. However, compared to 2020, their operation is less dispersed in 2050 (i.e. lower maximum and higher minimum), which is due to the larger network buffer capacity along with the increased role of sectoral integration and increased use of long-term hot-water storage in BE. Compared to 2020, the variation in the high-density (HD) network noticeably reduces, primarily because of a decrease in the use of gas-fired electricity generators. However, the HD network remains the main national medium for heating purposes in 2050; therefore, its behaviour resembles that of the MD network. Moreover, the large minimum operating value of the HD network relates to high levels of imports and exports (assumed to have a flat profile in this study), which indicates the key role of the Netherlands as a European natural-gas hub.

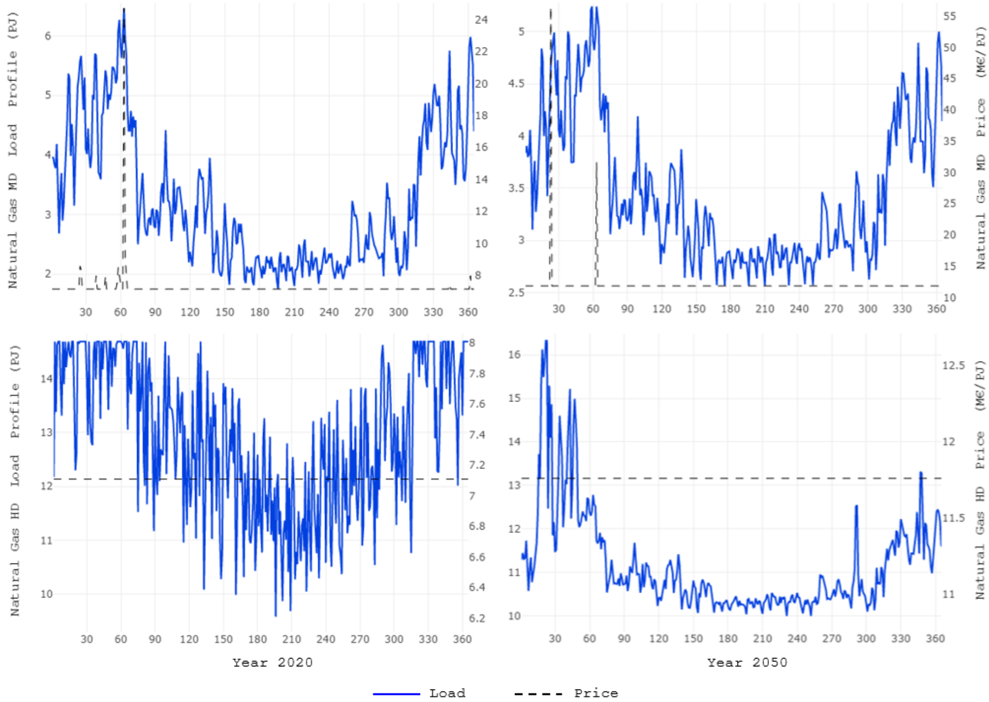

Figure 27, Daily loads and respective prices of natural gas networks in 2020 and 2050.

IESA-Opt represents the CCUS and hydrogen networks with daily balances, and its operation in 2050 is shown in Figure 28. Both hydrogen and CO_2 exhibit a seasonal behaviour owing to the availability of cheaper electricity in the summer. Lower electricity prices promote the use of electrolysers in the summer, which consequently triggers an increased use of CO_2 from the CCUS network to produce synthetic fuels. The high variability in the hydrogen network is due to its limited adoption (i.e. P2L). If hydrogen were to be adopted for more uses, the hydrogen buffer would become a more important measure for mitigating network expansion costs, thus resulting in a more homogeneous profile. Finally, the CCUS network exhibits a strong weekly pattern, which can be explained by its connectivity to industrial technologies, which were assumed to follow "low-weekend" operational profiles owing to the lack of available data for the industry sector.

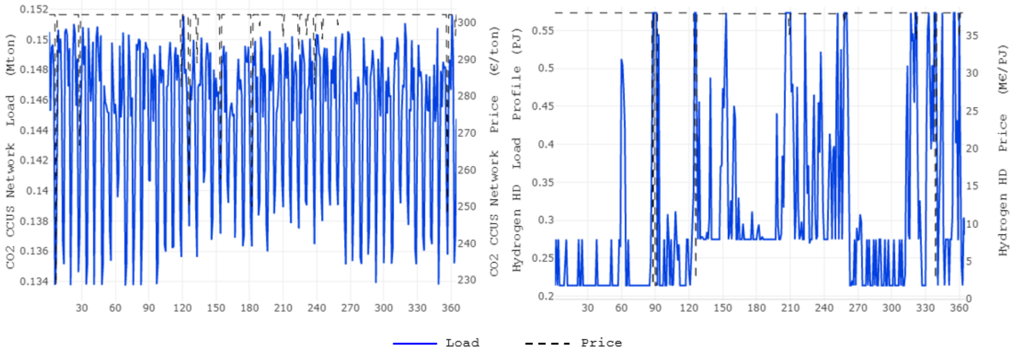

Figure 28, Daily loads and respective prices of CCUS and hydrogen networks in 2050.

4.3.6. **Power sector**

One of the advantages of the approach adopted in IESA-Opt is that it considers both the long-term and short-term dynamics of the power sector, the intra-year operation of which comprises a complex process that mixes demand-side and supply-side variabilities (e.g. VRES). The long-term supply is reported in Table 17, which shows the technologies used to generate electricity for the various network levels considered in the system[33]. This table shows that the entire system is being supplied energy almost entirely by VRES by 2050, while it still uses combined-cycle gas turbines for peak hours and complements the flexible supply with considerable amounts of CAES[34]. Another observation is that the required installed capacity of transformers increases as the generation becomes increasingly variable and decentralised. This means that although the conversion losses increase, the system requires considerable network flexibility to optimally balance supply and demand among all the options located at various voltage levels along the network (such as imports and exports, electrified industrial activities, and EVs).

[33] Only the annual generation values and technologies of the sector are reported in the table, which means that the generation of CHPs cannot be found in this table. The evolution of the installed capacities and the complete list of demand and supply technologies may be referred to on the web portal of the model [151].

[34] Storage technologies are not generators, but in this case, we are reporting the electricity from discharging.

Sector	Activity	Technology	Units	2020	2030	2040	2050
Power	High voltage	Offshore wind	PJ	14.0	176.3	554.7	736.2
		Coal old	PJ	53.2	0.0	0.0	0.0
		Co-fired coal	PJ	73.5	0.2	0.0	0.0
		Co-fired coal with CCUS	PJ	0.0	0.0	0.0	0.0
		CCGT	PJ	116.4	19.9	123.0	47.7
		CCGT with CCUS	PJ	0.0	0.1	0.3	0.1
		CCGT from BFG	PJ	5.2	0.0	0.0	0.3
		GT	PJ	0.1	0.0	0.0	0.8
		Nuclear	PJ	14.4	14.5	0.0	0.0
		Biomass	PJ	0.1	0.1	0.1	0.1
		Compressed-air above-ground storage	PJ	0.0	8.6	11.8	14.9
		Compressed-air underground storage	PJ	0.0	11.4	93.1	144.0
		Import from BE	PJ	8.8	5.9	12.2	38.2
		Import from DE	PJ	44.4	75.0	13.9	35.4
		Import from DK	PJ	7.8	7.2	8.8	11.4
		Import from NO	PJ	9.0	9.1	13.1	15.6
		Import from GB	PJ	1.0	5.5	9.4	15.3
		Transformers to HV	PJ	1.7	9.3	30.5	30.5
	Medium voltage	Hydro power	PJ	0.4	0.4	0.3	0.3
		Onshore wind	PJ	25.5	57.4	67.0	81.0
		Solar PV fields	PJ	3.1	13.8	37.8	67.2
		Industrial solar PV	PJ	5.9	42.0	84.0	112.0
		Transformers to MV	PJ	123.0	19.2	43.6	134.7
	Low voltage	Residential solar PV	PJ	9.8	56.0	112.0	168.0
		Transformers to LV	PJ	112.1	217.4	286.2	284.7

Table 17, Evolution of power sector configuration.

Another key capability of IESA-Opt is its ability to provide shadow prices for energy carriers, which is especially useful for electricity networks. These prices are obtained by solving the dual variables of the hourly balance constraints for the electricity grid, and they only represent the energy component of the dispatch, as there are no reserves depicted in the model. As an illustration of this capability, Figure 29 presents the 2020 and 2050 price duration curves for this scenario for the three electricity networks modelled in the Netherlands. There are two main observations to note here: the increase in prices and the wider spread of price events. The higher presence of VRES in the system triggers a significant number of hours with low electricity prices owing to the corresponding low marginal cost of operation. However, VRES cannot only satisfy the system demand of electricity, but also requires other elements of the system to operate: dispatchable units in the Netherlands and Europe, cross-border electricity flows, batteries and storage technologies, and cross-sectoral flexibility alternatives. It should also be noted that natural gas and CO_2 ETS prices are assumed to increase significantly by 2050 in the scenarios, which, in combination with the aforementioned flexible operation technologies, drive the increase in prices. It is interesting to note that the medium-voltage grid appears to present the highest number of events with low electricity prices in 2050. This indicates the highest potential for photovoltaics in this scenario, which was supposed to be available for connection in the medium-voltage grid. This is a clear example of how congestion points at different voltage levels of the grid (and, although not considered here, is even more important at different locations) can strongly influence the grid requirements for flexibility.

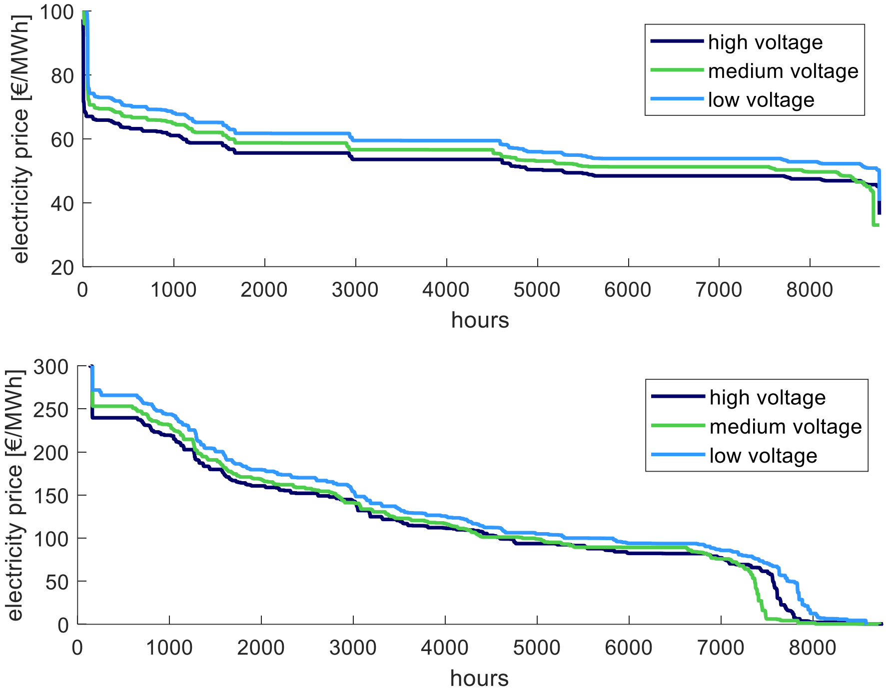

Figure 29, Duration curve of shadow prices for the different electricity networks considered in the Netherlands' power system representation. Top: Year 2020. Bottom: Year 2050.

The resulting system configuration presents a considerable increase in electricity flows, with almost triple the 2020 net system load by 2050. This effect is simultaneously driven by an increase in the external trading flows as well as by a profound electrification of both the final and energy sectors, as shown in Table 18. It can be observed that the Netherlands evolved from a net importer to a net exporter, with an increase in volume facilitated by the resulting interconnection capacity expansions[35]. Similarly, by 2050, the system more than doubles its electrification, which is triggered by the adoption of industrial technologies such as ULCOWIN and SSAS, (moderate) electrolyser use, deployment of the electric transport fleet, and choice of electric technologies for heating. Finally, it is worth highlighting that the maximum level of system curtailment is less than

[35] This scenario allows the model to double the existing interconnection capacities of the Netherlands after 2040.

50 PJ, which accounts for less than 5% of the electricity produced by VRES in 2050. Such efficient use of VRES electricity is fundamentally enabled because of the crucial role of cross-sectoral flexibility.

Electricity volumes	Units	2020	2030	2040	2050
System load	PJ	439.5	497.7	1065.3	1287.1
Imports	PJ	73.2	105.6	59.0	119.5
Exports	PJ	78.2	78.2	337.7	305.0
Net	PJ	434.5	525.1	786.5	1101.7
Final use	PJ	402.0	464.5	638.9	738.1
Curtailment	PJ	0.1	1.3	22.6	43.3
Average price	€/MWh	40.0	41.9	29.5	28.1
Price variability	€/MW	0.6	8.0	5.3	6.9
Total electrification	%	11.6	15.9	22.7	28.8
Final electrification	%	20.0	27.5	38.3	40.2

Table 18, Evolution of important electricity parameters.

4.3.7. **Cross-sectoral flexibility**

The ability to describe the sectoral potentials to provide system flexibility in allocating electricity from VRES is one of the key capabilities of IESA-Opt. Figure 30 presents the cost-optimal evolution of cross-sectoral flexibility volumes required to integrate a large share of VRES according to the archetypes considered in the model (Section 4.2.1.1). The most apparent result is the steep increase in the cross-sectoral flexibility in the system from a landscape in which only CHPs deviate from their hourly operation profiles to cope with the power system dynamics to a landscape in which almost all the archetypes are actively deviating. Only the flexibility of CHPs (provided by 13 technologies located in the waste, heat for services, heat for LT and HT, and agriculture subsectors) decreases by 2050, which is in line with the decrease in the use of CHPs. Furthermore, the shedding archetype exhibits the most pronounced role as a cross-sectoral flexibility provider and is mainly driven by the adoption of electrolysers for the hydrogen network, ULCOWIN for steel production, SASS for ammonia production, and in situ refineries' electrolysers for production of road fuels for export (as reported in Table 16). Similarly, storage also provides a significant amount of flexibility and is led by under- and above-ground CAES (as reported in Table 17). Finally, the transport sector also has a share in the contribution; however, it is primarily in the form of smart charging rather than vehicle-to-grid.

Cross-sectoral flexibility is a key capability of IESA-Opt, but it requires a significant amount of data gathering and technology description effort to be able to provide even more insightful analyses. The current flexibility descriptions in the model are focused on few technologies; therefore, it is recommended that the list of technologies that can provide flexibility be expanded. This expansion is expected to influence the lowering of transition costs and reshaping of cost-optimal system configuration.

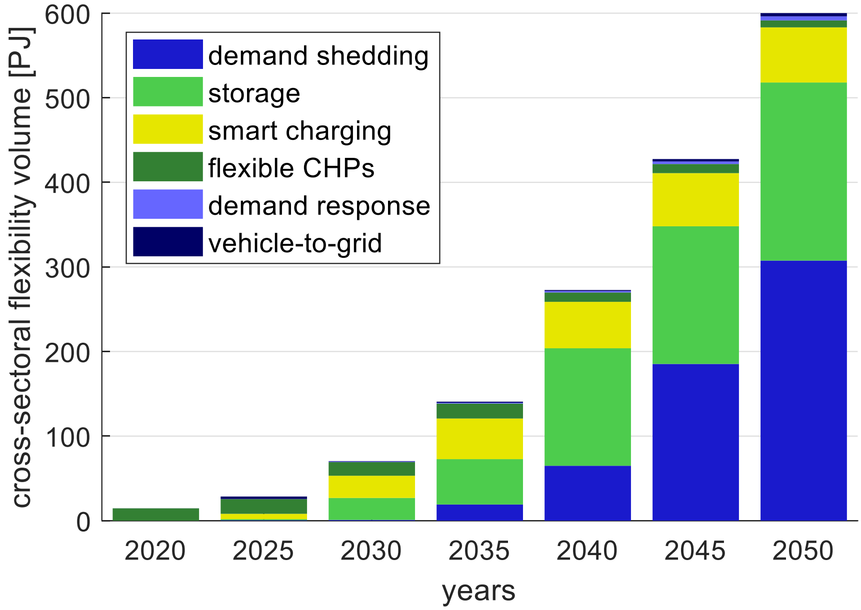

Figure 30, Evolution of the cross-sectoral flexibility volumes in IESA-Opt. This indicator measures the total amount of electricity demand that was displaced from the original operational profile. The storage volume reported in this graph corresponds to the charging electricity volume.

Using the hourly time-steps approach instead of the time-slice method, we can observe the seasonal behaviour of technologies, such as long-term heat storage. Figure 31 presents the load profile of the hot-water storage buffer that is connected to the low-temperature heat network. The seasonal trend indicates that the heat storage is charging when the heat demand is low during the summer months and discharging when the heat demand (and price) is high during winter months. The charging and discharging behaviours are directly related to the heat price (i.e. shadow price) of the LT network. Therefore, the storage discharges optimally when prices increase (assuming intra-year perfect foresight).

Other technologies such as ULCOWIN, SSAS, electrolysers, CHPs, and underground CAES demonstrate interesting seasonal behaviours that can be referred to online through the model’s portal.

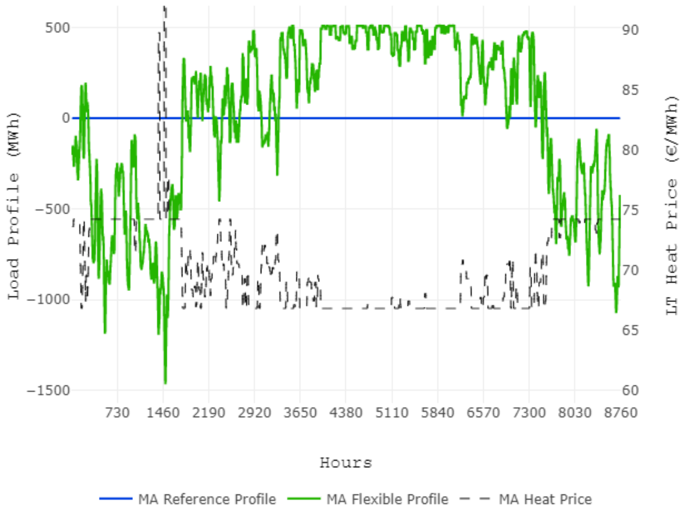

Figure 31, Daily moving average of hot-water buffer load profile and the respective heat prices in the LT heat network

The use of the hourly temporal resolution enables the model to analyse short-term flexibility options, such as the demand response. Figure 32 presents the load profile of the demand response on a random day. Here, the maximum shifting time frame is one day; hence, the sum of the area between the reference profile (i.e. blue line) and flexible profile (i.e. green line) is zero at the end of each day. Moreover, the flexible profile exhibits an increase in consumption at mid-day hours when the nodal electricity prices (i.e. shadow prices) are lower.

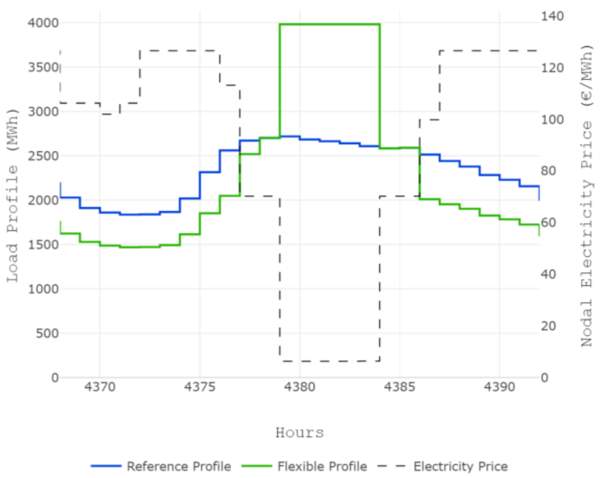

Figure 32, Reference and flexible profiles of demand response in residential sector in 2050.

4.4. Sensitivity Analysis

The results presented above correspond to the single run of the scenario presented in Section 4.2.2. However, the energy transition is strongly dependent on the denouement of uncertainties, and a practical method of addressing such uncertainties in optimisation models is via sensitivity analyses. To exemplify the usefulness of the model in this arena and explore the relevance of key elements observed in the results, we present four sensitivity exercises in this section: 1) the exploration of different climate policy targets for GHG emissions reduction under four scenarios with different levels of biomass and CO_2 storage availabilities; 2) an analysis of the impact of the different demand streams of oil and OBPs; 3) a bi-dimensional exploration of the role of imported biomass availability and its corresponding cost; and 4) the sensitivity around the demand drivers of key sectoral activities. Finally, it is important to mention that over 100 runs were required to build a different sensitivity analysis. Therefore, we optimised the energy system for the year 2050 only, and we could thus decrease the computational time from 8 h to 30 min per run.

4.4.1. Change in CO_2-reduction target from 80% to 130%

One of the most interesting features of the transition from the integrated-energy system perspective corresponds to the possibility of achieving negative emissions. To explore this topic, the following exercise presents an analysis focused on three aspects: the climate policy reduction target, the availability of biomass, and the availability of CO_2 storage capacity. This analysis is based on two modifications of the scenario described in Section 4.2.2, with different levels of CO_2 storage and biomass availability; the resulting four combinations are presented in Table 19, wherein the HCHB scenario uses the same values as the reference scenario used for the results in Section 4.3.

Scenario	**Description**	**2050 potentials**			
		CO_2 storage [Mton CO_2]	National wood [PJ]	Imported wood [PJ]	Imported biofuels [PJ]
HCHB	High availability of biomass and CO_2 storage	50	120	320	330
LCHB	High availability of biomass and low availability of CO_2 storage	25	120	320	330
HCLB	Low availability of biomass and high availability of CO_2 storage	50	60	0	0
LCLB	Low availability of biomass and CO_2 storage	25	60	0	0

Table 19, Description of the scenarios used for the sensitivity analysis presented in section 4.4.1.

These four scenarios were tested with different emissions reduction targets (i.e. ranging from no target to a 130% emissions reduction) in order to analyse the interaction between biomass and CO_2 storage with respect to the level of system decarbonisation. As a result of this exercise, Figure 33 demonstrates the objective function[36], shadow price of the emission constraint, average abatement cost[37] (AAC), and curtailment of intermittent renewable electricity generation.

The obtained results are relevant as they present the increase in system costs against different decarbonisation levels. For instance, the social costs increase between 2% and 8% owing to the current climate policy of 95% GHG emissions reduction and variation in the biomass and CO_2 storage availabilities. This highlights two findings: the significant impact of the biomass and CO_2 storage potentials in aiding the decarbonisation of the system affordably, and the significance of ensuring that biomass and CO_2 storage are generously available in the future, as this could not only aid in reducing transitional costs but also to aim for a more ambitious climate policy. This can be observed not only in the values of the different objective functions, but also in the fact that both the shadow price of CO_2 and the ACC for the LCLB scenario at the 95%-reduction target are almost identical as in contrast to the HCHB scenario with a 115%-reduction target.

Finally, an interesting result is that the curtailment in 2050 varies in the same range of 20–130 PJ per year for all four scenarios, where the lower availability of biomass and CO_2 storage results in a lower curtailment for each GHG-reduction target. The explanation for this is that the maximum deployment levels for VRES are reached for the four scenarios even when no target is being enforced. Therefore, a more stringent target results in a more extensive use of what would otherwise be curtailed electricity, as it makes expensive electrifying technologies more competitive.

For all these observations, both the LCHB and HCLB scenarios stay in the middle of the LCLB and HCHB results, suggesting that both potentials are equally important for decarbonising the system. However, it is also evident that, for scenarios with negative emissions, the availability of biomass is more beneficial for the system.

Analysis of the dynamics of electricity imports and exports is performed to expand the previous sensitivity study. Figure 34 presents a comparison of the import and export electricity flows for 2050 with respect to the increase in the emissions-reduction target for the four aforementioned scenarios. It is important to mention that, for all these runs, the installed capacities of the European nodes remained unchanged.

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[36] The objective-function value corresponds to the total system costs, which include the costs of the national energy system of the Netherlands plus the European power system costs and the costs of exported refined OBPs for the Netherlands.

[37] The average cost paid to stop emitting a ton of CO_2, obtained as the total system cost increase with respect to the uncapped scenario divided by the tones of CO_2 emissions avoided in each target scenario.

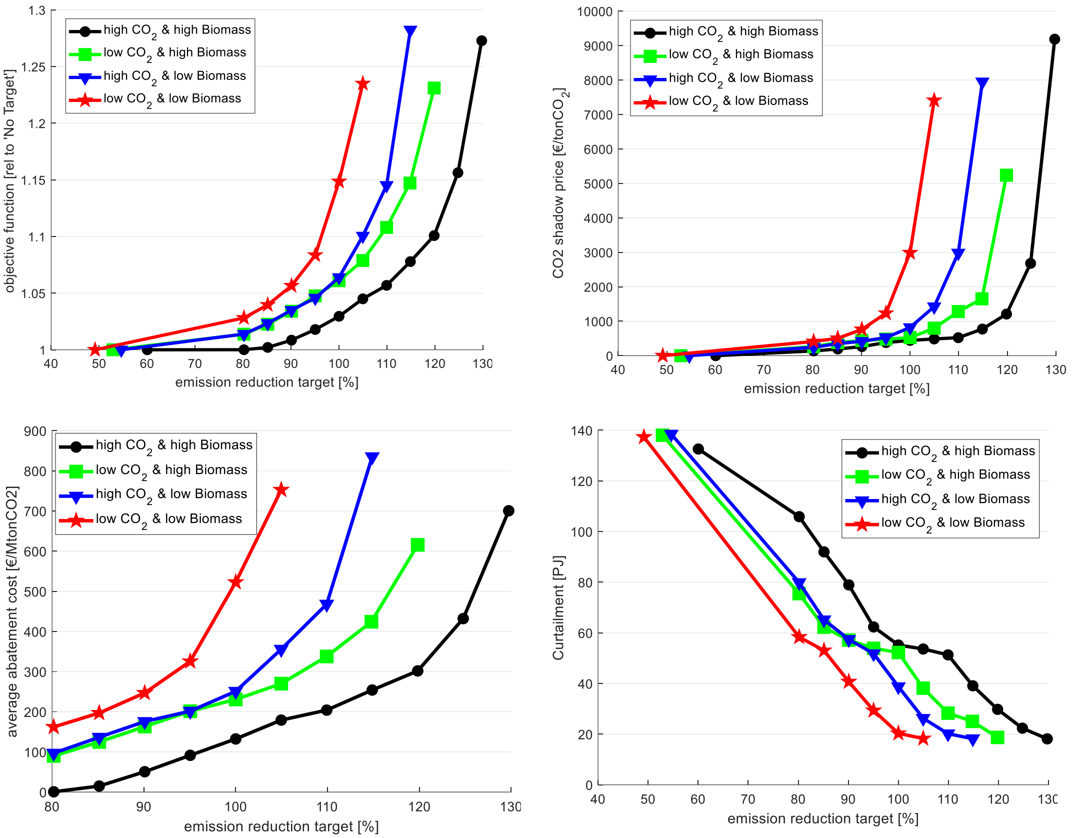


Figure 33, Results of the sensitivity analysis modifying emissions reduction targets and CO_2 storage and biomass availability in 2050.

The first observation is that the cases with the minimum and maximum targets present the same flows for all four scenarios, which hints at some possible maximum and minimum trading operation levels for the system. The second observation is the progressive increase in imports and a decrease in exports as the emissions-reduction target is increased. This happens because a looser target allows for cheaper electricity options that can compete in the European market over more hours, while at the same time, imported electricity is considered by the model as clean electricity since it does not increase the national emissions account.

A conclusion from this exercise is that a higher availability of CO_2 storage and biomass provides the system with an enhanced ability to export electricity. It can be observed that, for the same targets, the HCHB scenario exports more electricity than the LCHB and HCLB scenarios, which share similar trends, and the export flows are lower for the LCLB scenario.

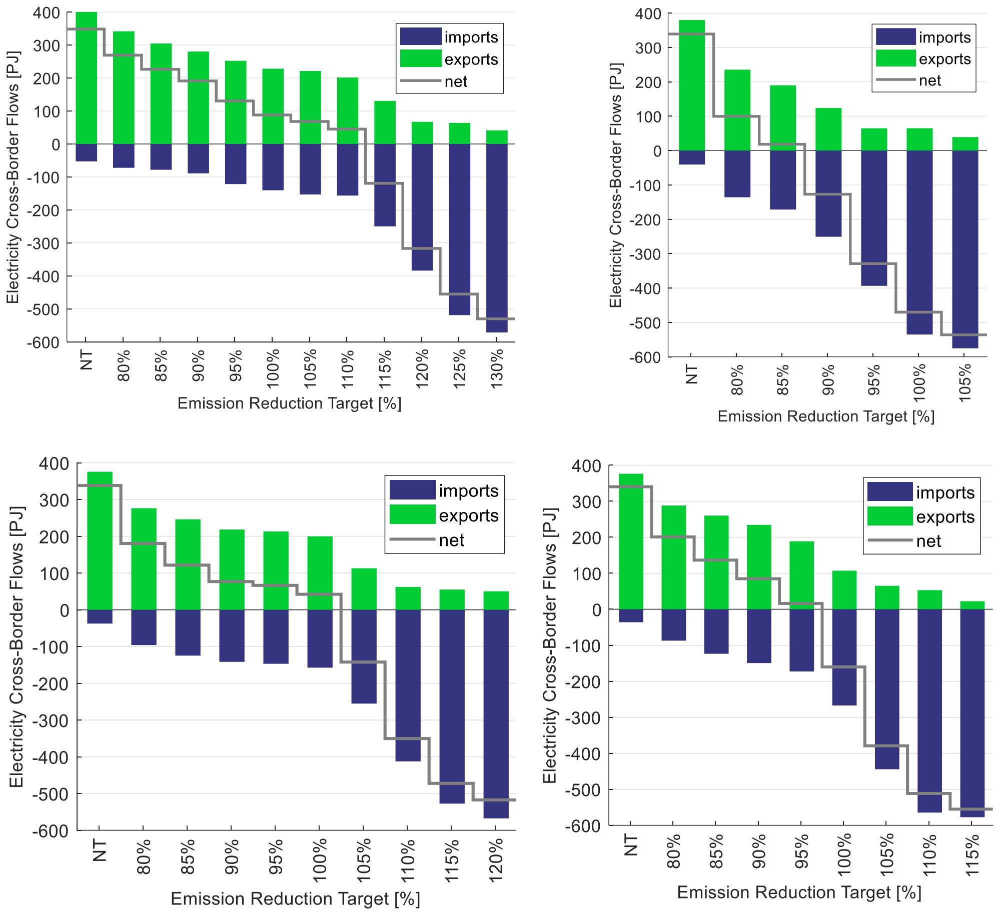


Figure 34, Import and export electricity flows in 2050 for the four scenarios with different emission targets. Top left: HCHB scenario. Top right: LCLB scenario. Bottom left: LCHB scenario. Bottom right: HCLB scenario.

4.4.2. **Sensitivity with respect to oil demand streams**

Even in a highly decarbonised scenario, as presented in Section 4.3, oil still plays a significant role in the energy mix. According to Figure 20, there are three main demand streams remaining in 2050 for oil or OBPs: kerosene for aviation, oil for refineries, and OBPs as feedstock for the petrochemical industry. These manage to bypass the emissions-reduction target as they hardly account for any emissions considered within the target. For instance, emissions from international transport are considered as national emissions only in international waters or for landing and take-off, which comprise less than a quarter of the total emissions. Furthermore, the refineries in the Netherlands export the majority of their produce, and the emissions resulting from the oil fuelling process are captured. Similarly, OBPs used for petrochemical feedstock are mostly embodied in the produce, and fuel-related emissions are treated with CCUS. Therefore, a parallel set of climate policies is required to address these topics. For this exercise, we analyse two different policies and a scenario description to measure their effects in the system: 1) a 95% emissions-reduction target for international transport, 2) a technology ban on oil-based processes for the petrochemical sector, and 3) the elimination of oil-based road-fuel exports by 2050. The scenarios adopted for this analysis are presented in Table 20, Scenario descriptions for the sensitivity analysis of oil demand streams..

Scenario	**Description**	**Total available biomass**	**Total available biofuels**	**National emission-reduction target**	**International transport emission reduction target**	**OBPs for feedstock in petrochemicals**	**OBPs exports**
		[PJ]	**[PJ]**	**[%]**	**[%]**	**[PJ]**	**[PJ]**
S_0	No added policy	1246	750	95	No Target	Unconstrained	3535
S_1	GHG reduction in international transport	1246	750	95	95	Unconstrained	3535
S_2	Ban on oil-based processes for petrochemical sector	1246	750	95	No Target	0	3535
S_3	Assumed elimination of OBP exports	1246	750	95	No Target	Unconstrained	0
S_4	All of the above	1246	750	95	95	0	0

Table 20, Scenario descriptions for the sensitivity analysis of oil demand streams.

For these scenarios, it was necessary to increase the biomass availability to ensure that sufficient biomass was available for use as feedstock in the petrochemical sector. For this, in addition to the 246 PJ of national available biomass, a maximum constraint of 1000 PJ was imposed on imported biomass. In addition, to enable sufficient availability of biofuels for international transport, the maximum constraint was increased to 250 PJ for bio-kerosene and 500 PJ for biodiesel.

The results of these sensitivity runs are presented in Figure 35, which shows the primary energy mix, system costs, and emission shadow prices. This figure shows that, irrespective of the scenario, the system uses all the available biomass. Furthermore, the system adopts bio-based feedstock extensively (76% of the feedstock comes from biomass in scenario S_o, and 67% in scenario S_3), which indicates that obtaining olefins from wood is close to cost optimality with an ETS emission price of 160 €/ton of CO_2 and an imported wood price of 16.91 €/GJ. It is also interesting to observe that, to (almost) completely eliminate oil use, it is necessary that the export of refined OBPs be eliminated while simultaneously setting a carbon policy on international transport emissions. If only one of the two occurs, OBPs are still a cost-effective alternative for the system, either as feedstock, as fuel for refineries exporting oil, or as kerosene for aviation. Finally, the adoption of natural gas in the mix is strongly influenced by the adoption of oil, as can be observed in scenario S_4, wherein the avoided emissions from OBPs increase the emissions budget and therefore the use of gas-fuelled applications (such as natural gas-powered combined-cycle gas turbines for power generation).

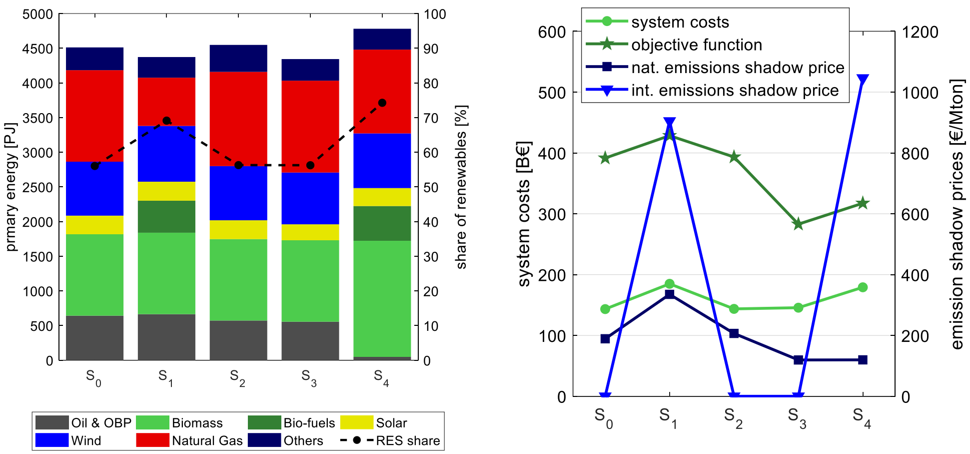


Figure 35, Sensitivity of the four sensitivity cases of oil demand streams. Left: Primary energy mix in 2050. Right: System costs and emission shadow prices.

Figure 35 shows that, from the perspective of cost, it is the international transport emissions policy what affects the objective function, the national system costs, and the national CO_2 shadow price the most. Significant increase in costs occurs only in scenarios wherein the international transport emissions are constrained. The other two elements of the analysis mostly resulted in the reconfiguration of the resources without strongly affecting system costs. This figure is a good method of explaining the difference between the objective function and the Netherlands' system cost. It can be observed that the objective functions of scenarios S_3 and S_4 (where there are no exports of OBPs) are considerably lower than those of the other scenarios. This happens because the disappearance of such considerable energy streams releases the objective function of a significant cost burden. However, the system costs of scenarios S_0 and S_3 are almost equivalent, where the only difference between them corresponds to the part of the export revenues that is lost due to the transformation added value[38] (approximately B€ 2). In addition, scenarios S_3 and S_4 report lower CO_2 shadow prices, which is explained by the avoided emissions from uncaptured GHG at refineries.

It is important to mention that, although power-to-liquids are present in the model, the technologies that are taken into consideration produce primarily road fuels and partially kerosene and residual oil products. It is necessary to include more technologies that can convert captured CO_2 to different forms of hydrocarbons using electricity. These technologies could reduce the biomass required by the system to fully displace OBPs and contribute to the easy and cheap integration of VRES.

4.4.3. **Impact of biomass resources availability**

The last two exercises presented in Sections 4.4.1 and 4.4.2 are clear examples of the importance of biomass for energy transition. However, real availability and costs are important uncertainties for an energy system. Therefore, we prepared a bi-dimensional sensitivity analysis of imported biomass while focusing precisely on availability and costs. For this, the sensitivity is built over the same reference scenario presented in Section 4.2.2 and comprises 72 scenario runs for eight values of imported biomass prices ranging from 4 to 48 €/GJ and nine values of biomass availability ranging from 0 to 1950 PJ/year.

The main results of these exercises are presented in Figure 36, where it is shown that biomass (imports) can help to significantly reduce the system costs for the Netherlands. In the extreme case, wherein imported biomass has a high availability (1950 PJ/year) at a very low price (4€/GJ), the objective function can decrease to 9% as compared to the extreme cases wherein there is no imported biomass available or it is extremely expensive (48 €/GJ). It should also be noted that, for this extreme scenario, the CO_2 shadow price approaches zero, indicating that an enforced clean energy system is almost as affordable as an unregulated energy system. For the "conservative area" of the graph, assuming 300 to 600 PJ/year of available biomass and prices between 12 and 20 €/GJ, the impact in the system was found to be significantly sensitive to these values.. In this region, we can find cost reductions of 0.2–0.5% and CO_2 shadow price reductions of 30 €/ton per 100 PJ of extra available imported biomass.

[38] This added value emerges from the energy cost perspective, and it fully neglects the commercial aspects behind the real revenues of energy exports.

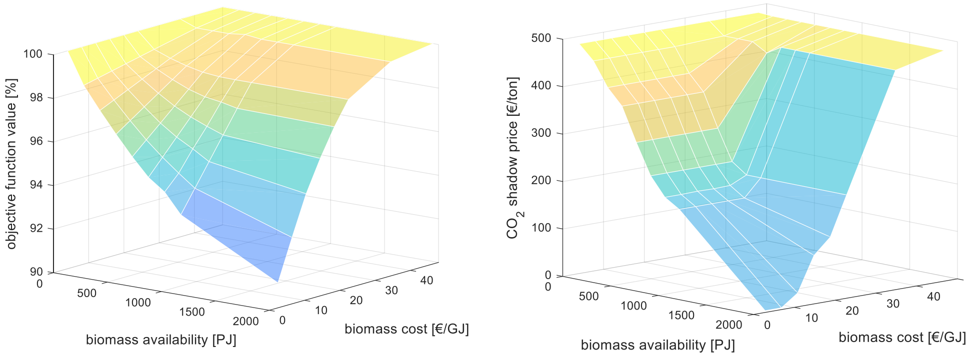


Figure 36, Impact of the imported biomass availability and its price on the transition costs for the Netherlands energy system. Left: Objective function (i.e. the national system costs, plus the operational costs of the European power system, plus the import costs and export revenues of other energy carriers for the Netherlands). Right: shadow price of emitted CO_2.

In terms of usage, the results are aligned with the expectations: there is a higher use of biomass when there is more biomass available and when this biomass is cheaper, as shown in Figure 37. However, a more interesting result is that there is an apparent minimum and maximum share of renewable energy in the primary mix in which these sensitivity scenarios move. For instance, when there is no biomass available or when it is available at high costs, the renewable energy share in the mix remains at 45%, and when there is a lot of biomass available at a very low price, the share in the mix increases to 65%.

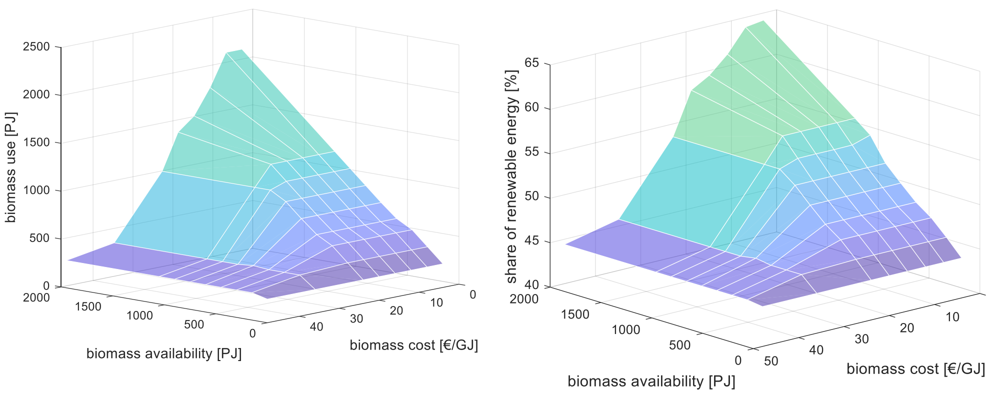


Figure 37, Impact of the imported biomass availability and its price on the total usage of biomass (left) and share of renewable energy in the primary energy mix (right).

It is important to clarify that the biomass in this study is considered as a renewable energy source with zero GHG emissions. The role of biomass as an alternative to aid in achieving deep system decarbonisation affordably would decrease if life-cycle emissions are accounted for, thus resulting in an emission-reduction potential of less than 100%. In addition, the availability of biomass for energy is strongly dependent on the food system and agricultural practices; hence, assuming high availability potentials neglects the competition for land between food and energy and most likely represents an unfeasible scenario.

4.4.4. **Sensitivity of 2050 demand drivers in key sectoral activities**

A key input required by the model that can strongly influence the model outcome is the assumed demand levels for different system activities. These assumptions play an even more important role after the coronavirus pandemic raised uncertainties around the expected development of different activities in the future economy. Therefore, we include a sensitivity analysis for the demand levels of the different activities within the different driver sectors, as shown in Table 21.

Sector	**Activity**	**Units**	**Value in 2050**				
			Reference	-20%	-10%	10%	20%
Agriculture	Electricity demand	[PJ]	47	37.6	42.3	51.7	56.4
Agriculture	Heat demand horticulture	[PJ]	101.5	81.2	91.35	111.65	121.8
Agriculture	Heat demand other	[PJ]	9.6	7.68	8.64	10.56	11.52
Agriculture	Machinery	[PJ]	30.2	24.16	27.18	33.22	36.24
Industry	Steel production	[Mton_Steel]	7.27	5.82	6.54	8	8.72
Industry	Non-ferrous production	[Mton_Al]	0.2	0.16	0.18	0.22	0.24
Industry	Ammonia production	[Mton_NH3]	3.35	2.68	3.02	3.69	4.02
Industry	Petrochemical transformation	[Mton_HVC]	8.7	6.96	7.83	9.57	10.44
Industry	Other ETS chemicals	[Idx_2020]	1.55	1.24	1.4	1.71	1.86
Industry	Other ETS	[Idx_2020]	1.13	0.9	1.01	1.24	1.35
Industry	Other non-ETS	[Idx_2020]	1	0.8	0.9	1.1	1.2
Industry	Machinery	[PJ]	49.5	39.6	44.55	54.45	59.4
Transport	Motorcycles	[Gvkm]	7.2	5.76	6.48	7.92	8.64
Transport	Passenger cars	[Gvkm]	125.3	100.24	112.77	137.83	150.36
Transport	Light-duty vehicles	[Gvkm]	32.3	25.84	29.07	35.53	38.76
Transport	Heavy-duty vehicles	[Gvkm]	8.25	6.6	7.43	9.08	9.9
Transport	Buses	[Mvkm]	650	520	585	715	780
Transport	Rail	[Mvkm]	230	184	207	253	276
Transport	Intra-EU aviation	[Mvkm]	430	344	387	473	516
Transport	Extra-EU aviation	[Mvkm]	850	680	765	935	1020
Transport	Inland-domestic navigation	[Mvkm]	90	72	81	99	108
Transport	International navigation	[Mvkm]	145	116	130.5	159.5	174
Transport	Other transport	[PJ]	30	24	27	33	36

Other emissions	CH_4 enteric fermentation	[Mton_CO2]	6.88	5.5	6.19	7.57	8.26
Other emissions	CH_4 manure management	[Mton_CO2]	3.22	2.57	2.9	3.54	3.86
Other emissions	N_2O manure management	[Mton_CO2]	0.65	0.52	0.59	0.72	0.78
Other emissions	N_2O Fertiliser	[Mton_CO2]	2.7	2.16	2.43	2.97	3.24
Other emissions	HFC Refrigeration	[Mton_CO2]	1.5	1.2	1.35	1.65	1.8
Other emissions	CO_2 others	[Mton_CO2]	2.2	1.76	1.98	2.42	2.64
Other emissions	CH_4 others	[Mton_CO2]	0.25	0.2	0.23	0.28	0.30
Other emissions	N_2O others	[Mton_CO2]	2	1.6	1.8	2.2	2.40
Other emissions	F-gas others	[Mton_CO2]	0.2	0.16	0.18	0.22	0.24

Table 21, Description of the scenarios used for the sensitivity analysis presented in section 4.4.4.

The impact of the demand volumes for each level is presented in Figure 38, which shows the change in the objective function with respect to the change in demand for each sector. Here, it is shown that both the transport and industrial sectors have the largest impact on the system, where respective changes of 4% and 2% in the objective function are observed when their demand increases or decreases by 20%. However, changes in the demand for activities within the agriculture sector and other emissions yield barely noticeable effects.

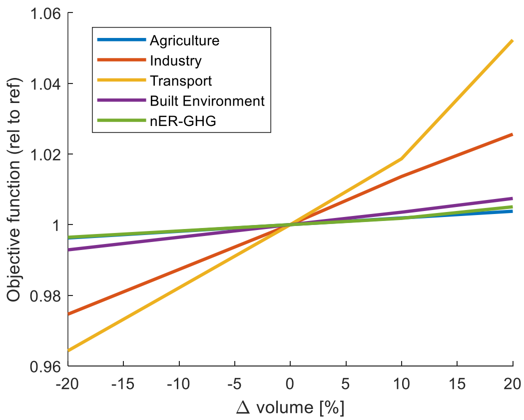


Figure 38, Behaviour of the objective function as a response to changes in 2050 demand of activities in some sectors of the system.

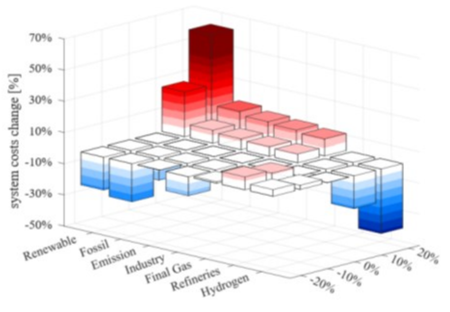
However, the fact that changes in a scenario do not result in significant changes in the objective function does not necessarily mean that the system configuration is not affected. Therefore, one of the most important advantages of using an integrated ESM with such a high level of granularity is that it allows us to track changes in other sectors, making it possible to identify possible cross-sectoral feedbacks. Figure 39 presents the impact that the demand deviations have on the sectoral costs of the most affected sectors.

Firstly, in the case of the industry sector (subfigure A), it can be observed that the demand deviations present a feedback proportional with the renewable, fossil, and final gas sectors, while it presents a negative feedback with refineries and subsequently hydrogen sectors. This increase in the required feedstock materials results in an increase in secondary refined products, which leads to a decrease in the production of electric fuels. Different results may arise if the model is equipped with technologies capable of producing ethylene and other petrochemical supplies from hydrogen or electricity.

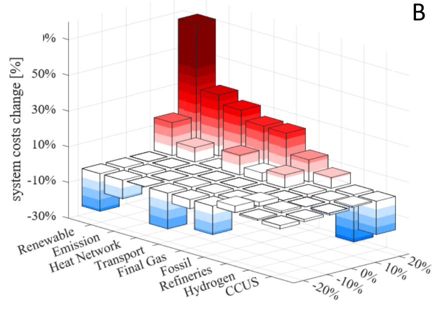
Secondly, changes in the transport sector (subfigure B) result in proportional feedbacks in the renewables, fossil, and final gas sectors. However, an interesting observation can be made in the case of refineries, which, owing to a substitution to oil refining from synfuel production, first presents a decrease and then an increase in the sector costs. Moreover, owing to an increase in non-ETS emissions when the transport demand increases by 20%, the residential and services sectors adopt district heating, thus increasing the sectoral costs of the heat networks.

Thirdly, the change in other emissions volumes (subfigure C) produces a substitution from fossil fuels to renewable energies. This change explains the trends in such sectors as well as the barely noticeable change in its "competing" non-ETS sector costs (namely, transport and residential sectors).

Finally, in the agriculture sector (subfigure D), lesser fossil fuels are used for machinery when the demand increases. This results in a lesser use of hydrogen in the system owing to the decreased use of synfuels, which explains the inverse feedback behaviour for this interaction. Moreover, the changes in the built environment demand appear to have negligible propagation effects on other sectors, as the changes are only apparent in the residential and services sectors.



A



B

C

D

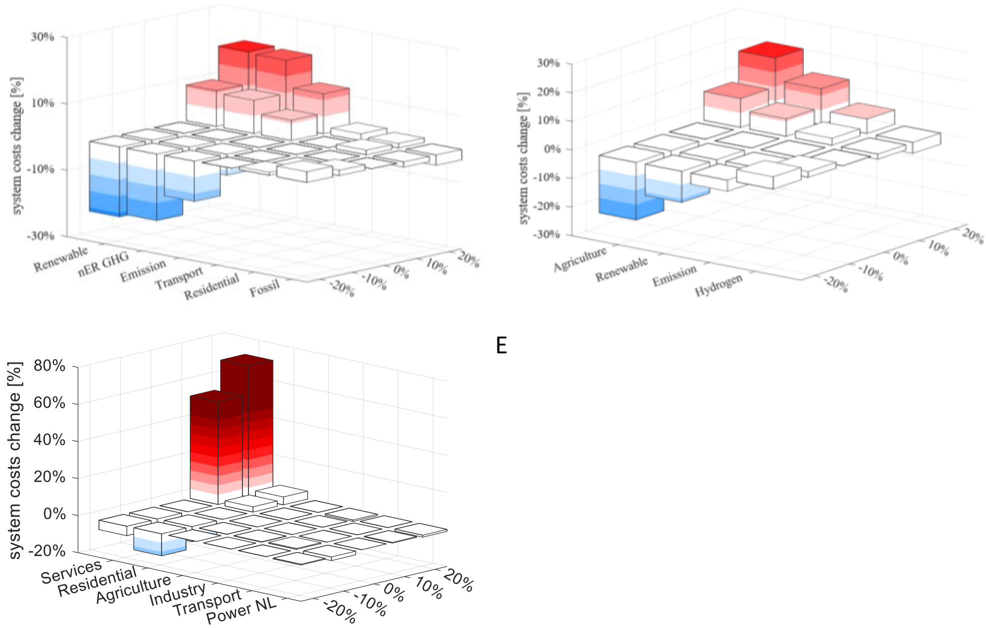


Figure 39, Changes in sectoral costs for different demand deviations for industry (A), transport (B), other emissions (C), agriculture (D), and built environment (E).

4.5. Discussion

To obtain all the above results, many runs were required, which consumed a significant amount of computational time. The main model run that produced the results presented in Section 4.3, which optimises the operation and planning for the period between 2020 and 2050 in five-year intervals with perfect foresight required under 6 h on a computer using a six-core processor, 32 GB of RAM, and an unblocked solid state drive. For the sensitivity analyses, the problem was solved only for the year 2050 to make it possible to collect a large number of data points, as a single-year run requires 20–30 min. However, this means that over 60 h of computational time was required to produce the 132 scenario cases used for the different sensitivity analyses. For each of these runs, the model was able to represent the electricity dispatch of the European power system and the cross-sectoral flexibility technologies that contribute to adopting higher levels of VRES simultaneously with the capacity planning of the system for the year 2050, using a complete energy system representation that accounts for all emission forms in every sector. These sensitivity exercises are perfect and practical examples to explain why IESA-Opt also presents a significant methodological improvement, as its computational agility opens up new possibilities.

IESA-Opt is suitable for many stand-alone applications, such as for exploring the role of public subsidies to achieve decarbonisation targets; determining future possible load profiles for the system owing to the influence of EVs, electric heating, industrial transformation, and cross-sectoral flexibility technologies; the effect of uncertain demand projection in system costs and emissions reduction targets; and specific sectoral analysis to identify ideal operational planning and optimal technology choices among several possible options. Furthermore, under the IESA framework depicted in Figure 14, this model can be used in collaboration with other models or under specific adaptations of its methodology for application in broader studies, such as a collaboration with macroeconomic models to quantify the feedbacks between the energy transition and GPD or employment; identification of national and regional constraints imposed by spatially sensitive parameters with the aid of spatial models and tools; and integration with agent-based simulation models for measuring the deviation between behavioural trends and social optima and the role of policy toolboxes in mitigating such deviations.

Nevertheless, it is important to mention that both the model and the analysis present some limitations. Firstly, wind energy is the largest share of the 2050 energy mix, relying mostly on offshore wind power generation. However, this analysis describes offshore wind as a single technology without considering different cost profiles based on spatial potentials, this can affect both the Netherlands and the North Sea power dispatch considerably, as well as the costs of the transition [169]. Secondly, we adopted an LP formulation, which does not take into consideration the unit commitment (MILP) for describing the operation of thermal generators. Secondly, we did not model reserves in the power sector, which can affect the outcome of the system configuration and thus the transition costs. Similarly, we assumed perfect foresight for modelling the energy transition, and thus, no forecasting errors were included in the operation profile predictions. This is another source of extra transition costs when dealing with large amounts of VRES in the system. In addition, for this analysis, we only used one climate year for all the VRES availability profiles in the whole transition; thus, we neglected the impact of climate change on resource availability and the different operation settings that the system might confront. Furthermore, the technological description is not yet fully extensive, as industrial activities should be further disaggregated to account for more decarbonisation technologies and further cross-sectoral synergies (e.g. mode-flexible processes such as smelters, paper mills, and local waste heat-recirculation networks). Finally, technological costs are exogenous, and thus, the model cannot account for the negative feedback from technological learning if investments are postponed until the last part of the transition. Therefore, the technology cost descriptions are a key component of the scenario definition, and owing to the extensive portfolio of options, there is no sensitivity analysis included in this study to address this issue.

To address some of these limitations and expand the reach of the possible analyses, there is a list of further improvements that can be made to the model. Firstly, we intend to focus on increasing the resolution with respect to industrial activities' descriptions. In addition, we are already expanding the geographical scope of the model by including all the countries around the North Sea to better account for European flexibility, offshore installations, and hydrogen development paths. We also intend to link the model with a macroeconomic module to account for important feedbacks with the economy, such as prices of commodities' prices and demand volumes. It is also important to mention that, given the wide energy system definition of IESA-Opt, it is sensitive to the data quality fed into the model;[39] hence, collecting, managing, and maintaining the database comprises a process of continuous improvement. This expands the scope for improvement and opens the door for other potential future research efforts. For instance, currently, the available data of the hourly demands of certain technologies are too generic (e.g. standard load, day and night, and flat profiles are applied to many technologies owing to the lack of available data) and could be improved, which could yield interesting studies on the evolution of demand profiles in the transition. Furthermore, the EV technologies and infrastructure catalogue could be expanded to compare the cost-effectiveness of options.

4.6. Conclusion

IESA-Opt is an adequate tool for analysing the impact of cross-sectoral flexibility in an integrated energy system in the Netherlands, which helps in understanding ways to further accommodate large amounts of variable renewable electricity. As an evidence of this, IESA-Opt was applied in this case study to determine the behaviour of energy system transition when taking into consideration interactions in terms of energy usage, emissions, and costs, while considering intra-year dynamics of the dispatch and operation of the power dispatch, gaseous networks, and cross-sectoral flexibility. Following are the two most relevant highlights of these results: 1) even in a high decarbonisation scenario, fossil fuels remain largely used as many causal factors such as international transport, exports of refined products, and industrial feedstock are not included in current climate policies in the Netherlands; 2) there will be a pivotal switchfrom fuel costs to capital costs in the energy transition that is mainly driven by electrification and the adoption of "fuel-less" renewable energy sources and technologies that can provide cross-sectoral flexibility.

In addition, several sensitivity analyses were performed to highlight the critical role of biomass and CCUS in achieving negative emissions to highlight the importance of including different demand streams for oil in the climate policy packages and to quantify the

[39] The complete model database is available in the online user interface [151].

uncertainty of key demand volumes for different sectors. From these, the most significant learning is that in order to displace oil-based products from the energy mix, a policy package comprising international transport, feedstock for high-value chemicals, and refined oil products exports is required in top of the current emission reduction targets. However, to make this transition affordable and effective it is necessary to ensure the availability of biomass resources together with the development of carbon capture and storage technologies. These findings are very relevant to help guiding the energy transition and are worthy to further exploration by means of further expansion of IESA-Opt capabilities as well as by the linking of the model with other analytical tools.

Measuring accuracy and computational capacity trade-offs in an hourly integrated energy system model [40]

Abstract

Improving energy system modeling capabilities can directly affect the quality of applied studies. However, some modeling trade-offs are necessary as the computational capacity and data availability are constrained. In this chapter, we demonstrate modeling trade-offs resulting from the modification in the resolution of four modeling capabilities, namely, transitional scope, European electricity interconnection, hourly demand-side flexibility description, and infrastructure representation. We measure the cost of increasing resolution in each capability in terms of computational time and several energy system modeling indicators, notably, system costs, emission prices, and electricity import and export levels. The analyses are performed in a national-level integrated energy system model with a linear programming approach that includes the hourly electricity dispatch with European nodes. We determined that reducing the transitional scope from seven to two periods can reduce the computational time by 75% while underestimating the objective function by only 4.6%. Modelers can assume a single European Union node that dispatches electricity at an aggregated level, which underestimates the objective function by 1% while halving the computational time. Furthermore, the absence of shedding and storage flexibility options can increase the curtailed electricity by 25% and 8%, respectively. Although neglecting flexibility options can drastically decrease the computational time, it can increase the sub-optimality by 31%. We conclude that an increased resolution in modeling flexibility options can significantly improve the results. While reducing the computational time by half, the lack of electricity and gas infrastructure representation can underestimate the objective function by 4% and 6%, respectively.

[40] This section is published in the Advances in Applied Energy journal (https://doi.org/10.1016/j.adapen.2021.100009)

5.1. Introduction

Increasing the share of VRES is one of the pathways to meet long-term decarbonization targets. As the share of VRES increases, the fine temporal resolution and detailed technological representation of ESM can have a substantial impact on analyzing dispatch and flexibility options such as short-term storage, seasonal storage, DSM, VRE curtailment, and cross-border trade. Further electrification of the energy system increases the need for analyzing sector coupling technologies such as P2Heat, P2Gas [170], P2Hydrogen [171], P2Chemicals, and P2Mobility [172]. Moreover, centralized or decentralized [173] infrastructural constraints can considerably affect long-term energy system planning [174].

Optimization ESMs have been used extensively in the energy modeling community, focusing either on the planning or operational aspects of the energy system. However, high temporal granularity (e.g., hourly time steps) and operational details (e.g., ramping constraints) are usually neglected in these long-term energy system models [175]. Therefore, they cannot adequately address operational constraints for long-term planning problems; for instance, the effect of flexibility options on energy system investment decisions.

The analysis of flexibility options in the energy system requires enhanced modeling capabilities. However, enhancements can be constrained by several factors, such as data availability and computational capacity. Consequently, based on the focus of the model, modelers have to make various simplifications in parameters such as the temporal resolution, technological details, spatial constraints, and underlying methodology. These simplifications can have a substantial impact on the energy system analysis in terms of feasibility and sub-optimality of results and calculation times. Therefore, a modeling trade-off should be made to maintain the balance between available resources and the required accuracy of the results.

Although several studies have investigated energy system modeling trade-offs, each of them neglects some energy system parameters that can affect the results. For instance, one study shows that increasing the temporal resolution in a power system model with high penetration of intermittent renewables can result in increased power system costs [176]. Similarly, another study shows a substantial reduction in baseload power investment as the temporal resolution increases from coarse time slices to hourly [177]. Another realizes the spatial trade-offs in power system modeling [178]. However, these studies neglect the interdependencies of the power system and other energy sectors. Another study quantifies the impact of improving the temporal resolution and operational details for varying penetration levels of intermittent renewable energy sources (IRES) [111]. However, it disregards the grid and cross-border trade. Another study illustrates the impact of temporal resolution on the share of renewables and CO_2 emissions using three different energy models [179]; however, it neglects the interconnection with neighboring nodes and countries. Other studies show that the absence of operational constraints in an energy system model underestimates wind curtailment and overestimates baseload plants [180]; however, it links a power system model with an energy system model by soft-linking method, neglecting real-time energy system interdependencies.

The novelty of this study lies in the quantification of some modeling trade-offs by employing an applied energy system model that covers the mentioned gaps, namely, covering all energy sectors, including grid infrastructure, and integrating a transnational linear power system representation that includes cross-border trade. We apply a reference scenario of the Netherlands as a case study, while the results can be interpreted for other similar national energy systems.

We use the IESA-Opt model, which is part of the IESA modeling framework [98] and can be used to quantify the value of flexibility in long-term energy system analysis. Among all the modeling capabilities of IESA-Opt, four are discussed in this chapter. First, the transitional scope (i.e., multi-period solve) allows the incorporation of multi-period factors such as technological lifetime, decommissioning, technological learning, and efficiency improvements, in energy models. At the expense of a higher computational load, the transitional model enables pathway conclusions to be drawn, such as optimal periods to invest in certain technologies. Second, integrating European electricity dispatch with the national ESM provides cross-border trade flexibility at hourly time-steps. Several national ESMs represented the power generation sector of neighboring countries by including their dispatch decisions (e.g., [1]). In highly interconnected systems (e.g., northwest Europe), neglecting cross-border trade or having a static representation of cross-border flows can lead to inaccurate technology portfolio and system cost estimates [2]. Third, a detailed description of flexibility options at hourly time-steps is necessary for modeling the integration of high shares of VRES [3]. Moreover, modeling all energy system flexibility options such as P2Heat, P2Mobility, P2Liquid, and P2Gas is necessary to accurately estimate energy storage needs [181]. IESA-Opt includes a detailed list of flexibility options (fully described in Table 23) divided into six main groups: flexible CHPs (11 technologies), shedding (6 technologies), demand response (2 technologies), storage (3 technologies), smart charging (3 technologies), and V2Grid (1 technology). Finally, the inclusion of infrastructural constraints allows the system to account for infrastructure development costs. The existing infrastructure is not fully compatible with a low-carbon energy system mainly due to the lack of CCUS and hydrogen networks [4]. All four capabilities can have major effects on the long-term planning of the energy system.

This study aims to measure the cost of increasing resolution in each modeling capability in terms of computational time and energy system modeling indicators, notably, system costs, emission prices, electricity generation, and import and export levels.

With this aim, in Section 2, we provide a brief introduction to the model, followed by a scenario description in Section 3. Then, in Section 4, we generate several cases for each of these four capabilities. Section 5 demonstrates the impact of enabling and disabling each of these capabilities on system configuration indicators. Finally, we draw a conclusion on modeling choices for a low-carbon energy system based on project aims and available computational resources.

The model's source code, along with its database and all the results, is accessible through the online portal of the model [151].

5.2. Brief introduction to the IESA-Opt model

This open-source national model uses the linear programming (LP) method to simultaneously optimize the short-term hourly operation and long-term 5-year interval planning problems from 2020 to 2050. The model includes multi-period techno-economic data of more than 700 technologies, in which 335 technologies represent all energy sectors of the Netherlands (as well as key cross-sectoral technologies such as P2Heat, P2Gas, P2Hydrogen, P2Liquids, P2Mobility, and V2Grid), and 365 technologies represent the electricity dispatch of EU countries in 20 nodes. The model accounts for emissions from non-energy sources such as enteric fermentation, fertilizers, manure management, and refrigeration fluids, as well as emissions from energy sources divided into national and European ETS, and non-ETS emissions. The energy infrastructure is modeled in ten networks for different pressures of natural gas, hydrogen, CCUS, and heat, and different voltage levels of electricity.

The main goal of IESA-Opt is to quantify the cost-optimal path for an integrated energy system transition towards a highly decarbonized future in which country-specific emission reduction targets are met. In addition, the model must be able to select from a very rich technology pool of options and be able to deal with the operational complexity of VRES. This means that the tool output consists of two main components. First, the optimal planning of the technology stocks that the system requires to satisfy economic activities in the transitional period. Second, the optimal intra-year operation of such a technological stock. This interaction between the short- and long-term decisions at an integrated level for the entire energy system makes it possible to simultaneously provide high temporal and technological granularities, which is the main contribution of the model to the scientific sphere.

IESA-Opt uses the LP approach and saves the computational capacity for increasing temporal and technological details of the energy system. Conventional large-scale long-term planning energy system models frequently use LP methodology to avoid excessive computational loads. Operational energy system models, especially power system models, tend to employ mixed-integer linear programming (MILP) methodology to account for binary or integer variables such as investment and unit-commitment decisions. The choice of LP over MILP methodology can considerably reduce the computational time while having a negligible impact on the modeling results, especially in energy systems with high shares of VRES [101]. The computational time of the LP formulation can be significantly lower than that of the MILP approach while providing relatively high precision in modeling relevant flexibility options [102].

The conceptual representation of IESA-Opt is illustrated in Figure 40. The modeling framework differentiates between driver activities and energy activities. Driver activities indicate the energy demand in the system (e.g., the production of steel or the use of passenger cars), while energy activities correspond to specific forms of energy carriers (e.g., electricity or hydrogen). The model requires the projected volumes of the driver activities as input to endogenously determine the optimal portfolio of technologies to meet the energy demand.

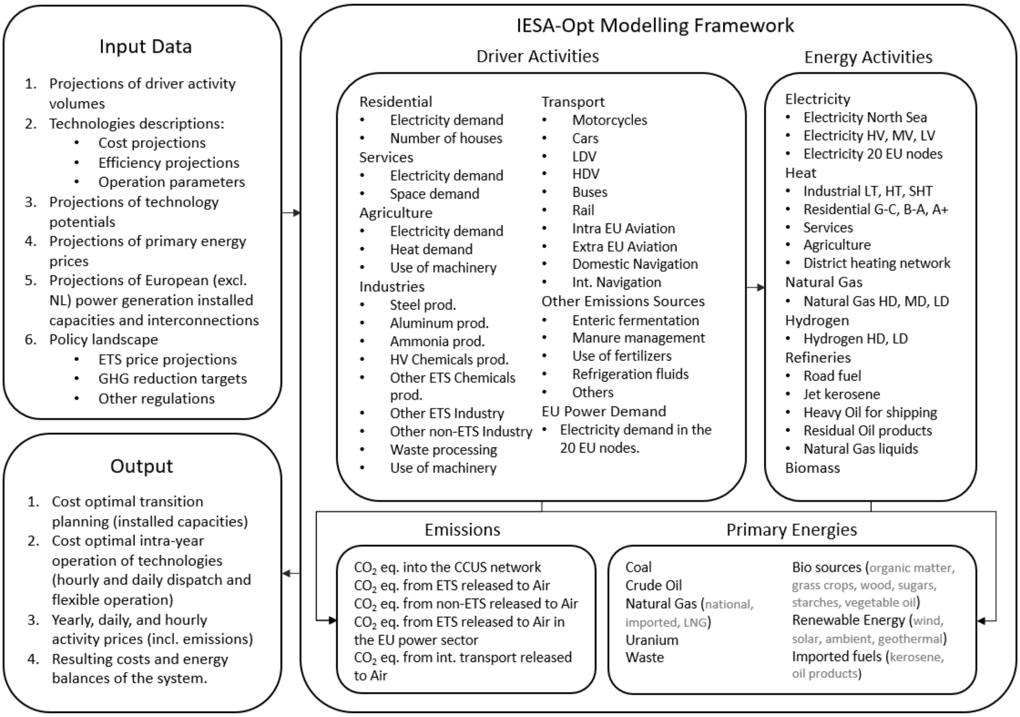


Figure 40, Conceptual framework of the IESA-Opt model.

5.3. Reference scenario

To facilitate the analysis of the impact of considering detailed European interconnectivity, cross-sectoral flexibility, and infrastructure representation in IESA-Opt, the reference scenario used for this chapter focuses on the adoption of a large share of VRES to produce electricity. Here, we present a brief description of the reference scenario, including the Netherlands's energy demand, EU power capacities, and seasonal and daily power loads in 2050. The detailed scenario definition is presented in Appendix A.

5.3.1. **Scenario storyline**

The projected development and part of the resource costs are extracted from JRC's POTEnCIA central scenario for the Netherlands [154], drawn accordingly with GDP growth rates presented in the 2018 ageing report [155]. Such projections lean towards business-as-usual economic development, which would fall within the narrative of the second shared socioeconomic pathway (SSP2) [156]. The costs of biomass were extracted from the reference storyline of the ENSPRESO database [157], as well as most of the considered potentials for renewable technologies in the Netherlands.

The environmental policy landscape of the Netherlands is presented by the Dutch government in the National Energy and Climate Plan (NECP) [158] and sets targets of 49% and 95% emission reductions for 2030 and 2050, respectively, as compared with 1990 levels. Furthermore, there seem to be no short or mid-term plans to further expand nuclear power and it will most probably disappear from the energy mix after 2033 [160]. In addition, the climate agreement voids the use of coal for power generation after 2030, although it is not yet fully clear if it will be allowed in combination with CCUS. Therefore, coal power plants are not allowed after 2030 in the scenario, while investment in coal with CCUS remains an option.

The technology-specific parameters refer to the activity inflows and outflows of each technology (energy or commodity balance) and the cost levels of the technologies (investment, fixed operational, and variable operational costs). The reference scenario uses data from central scenario descriptions of different sources. Most of the technologies described in IESA-Opt are based on the reference scenario of the ENSYSI model [28], where low-carbon technologies experience a learning rate of at most 20%. Technology data projections of the transport sector are obtained from the POTEnCIA central scenario [154]. In addition, data projections for technologies such as P2Liquid alternatives, electrolyzers, and direct-air-capture units are obtained from TNO's technology factsheets [163]. The complete technology data assumptions, as well as the link to the sources, can be found in the online portal of the model.

As IESA-Opt dispatches electricity for the entire EU, the climate targets of EU member states' power systems can also influence national power system development. Member states must cope with EU targets, but further voluntary contributions might vary, and such a variety of responses might strongly influence the outcome of the model, as the level of discrepancy in national policies might result in price differences and therefore highly imbalanced import and export flows. To cope with this, the reference scenario considers

EU generation assets from the MAF 2016, and the sustainable transition scenario runs until 2035 [114], which is then complemented with updated data from the national trends TYNDP scenario 2020 for the year 2040 [165]. Based on this configuration, we then run a highly decarbonized capacity expansion plan for all of Europe for the years 2040, 2045, and 2050 to ensure that the EU's assets are aligned with the Netherlands' assets. In this way, we avoid highly unbalanced electricity import and export situations due to modeling discrepancies.

5.3.2. **Energy demand in the Netherlands**

The energy demand in IESA-Opt is derived from certain economic drivers, which require an energy supply. The model considers national economic activities for the residential, services, agricultural, industrial, and transport sectors, as shown in Table 22 These activities are endogenously translated to energy requirements by the model, based on the choice of technology. For instance, there is an exogenous requirement to produce 7.3 Mton of steel in 2050. This amount of steel can be produced using several technologies such as blast furnaces, blast furnaces with CCS, Hisarna, Hisarna with CCS, and Ulcowin. Each of these technologies has a different energy balance. The model optimally decides which technology is the best to be used, considering several parameters such as its costs, efficiency, and emissions.

In addition to national economic activities, the model requires the expected demand for electricity in European countries as an input. The model requires electricity demand data on the following European countries: United Kingdom, Norway, Denmark, Germany, Belgium, Ireland, Sweden, France, Switzerland, Austria, Poland, Czech Republic, Slovakia, Spain, Portugal, Italy, and Finland, as well as aggregated figures on Baltic countries, Balkan countries within the EU, and Balkan countries outside the EU.

Sector	Driver	Units	Values				Source
			2020	2030	2040	2050	
General	Heat degree days	[HDD]	2900	2800	2700	2600	[182]
Residential	Appliances electricity demand	[PJ]	66.0	68.7	70.6	71.8	[183]
	Number of houses	[Mhouses]	8.2	8.8	9.2	9.6	[183],[162]
Services	Appliances electricity demand	[PJ]	138.4	137.6	138.9	143.9	[183]
	Used space	[Mm^2]	513.0	538.7	554.5	559.1	[183]
Agriculture	Appliances electricity demand	[PJ]	29.0	30.2	31.2	32.6	[183]
	Heat demand for horticulture	[PJ]	106.9	111.2	115.4	123.0	[183] ,[162]
	Heat demand for agriculture	[PJ]	8.4	8.7	9.0	9.6	[183] ,[162]
	Machinery consumption	[PJ]	27.1	27.8	28.5	30.2	[183]
Industry	Steel production	[Mton]	6.9	6.7	6.8	7.3	[183]
	Aluminum production	[Mton]	0.2	0.2	0.2	0.2	[183] ,[162]

Sector	Driver	Units	Values				Source
			2020	2030	2040	2050	
	Ammonia production	[Mton]	3.2	3.4	3.6	3.8	[184]
	High value chemicals production	[Mton]	8.5	9.4	9.7	10.0	[183] ,[162]
	Other ETS chemical industry	[Index]	1.1	1.3	1.4	1.7	[183] ,[162]
	Other ETS industry	[Index]	1.0	1.1	1.1	1.2	[183] ,[162]
	Other non-ETS industry	[Index]	1.0	1.0	1.0	1.0	[183] ,[162]
	Machinery consumption	[PJ]	24.5	27.4	28.6	29.4	[183]
Waste	Waste incineration	[Mton]	7.6	9.1	10.6	12.3	[183] ,[162]
	Waste sewage	[PJ]	3.7	4.3	4.9	5.6	[162]
	Waste landfill	[PJ]	0.4	0.0	0.0	0.0	[162]
Transport	Motorcycles	[Gvkm]	5.1	5.8	6.5	7.2	[183]
	Passenger cars	[Gvkm]	103.4	107.0	111.7	117.4	[183]
	Light-duty vehicles	[Gvkm]	21.2	24.3	27.4	32.3	[183]
	Heavy-duty vehicles	[Gvkm]	7.0	7.4	7.8	8.8	[183]
	Buses	[Mvkm]	617.2	606.0	616.1	650.6	[183]
	Rail	[Mvkm]	168.7	195.2	221.1	231.9	[183]
	Intra-EU aviation	[Mvkm]	211.5	264.2	344.5	432.2	[183]
	Extra-EU aviation	[Mvkm]	668.5	740.5	794.0	848.2	[183]
	Inland-domestic navigation	[Mvkm]	54.6	70.1	81.0	92.8	[183]
	International navigation	[Mvkm]	112.9	124.7	135.3	146.3	[183]
Power EU	EU electricity demand	[EJ]	11.7	11.8	12.0	11.9	[114]

Table 22, Activity volumes considered in the Reference Scenario.

5.3.3. **Daily and seasonal power load curves**

The electricity demand is an endogenous parameter in IESA-Opt, giving the model the ability to decide the optimal level of electrification. However, the model distributes the demand based on an exogenous normalized load profile. The total national load profile is endogenously calculated in the post-processing as the sum of the hourly profile of all electricity consumer technologies in the system. Therefore, the load profile can vary from scenario to scenario. These demand profiles are briefly described as follows.

In IESA-Opt, the normalized electricity load profile of each country can vary at each hour of the year. These profiles are exogenous to the model and we assume they remain the same for all periods up to 2050. Figure 41 demonstrates the yearly normalized (i.e., the sum of all hourly loads in a year is equal to one) electricity load profile for all EU nodes in the IESA-Opt model. Southern countries such as Italy and Spain are assumed to have higher loads in summer, mainly due to the need for electrified cooling. We assume northern countries such as Great Britain, Norway, Sweden, and Finland to have strong seasonal variability, while other countries have a milder load profile during the year.

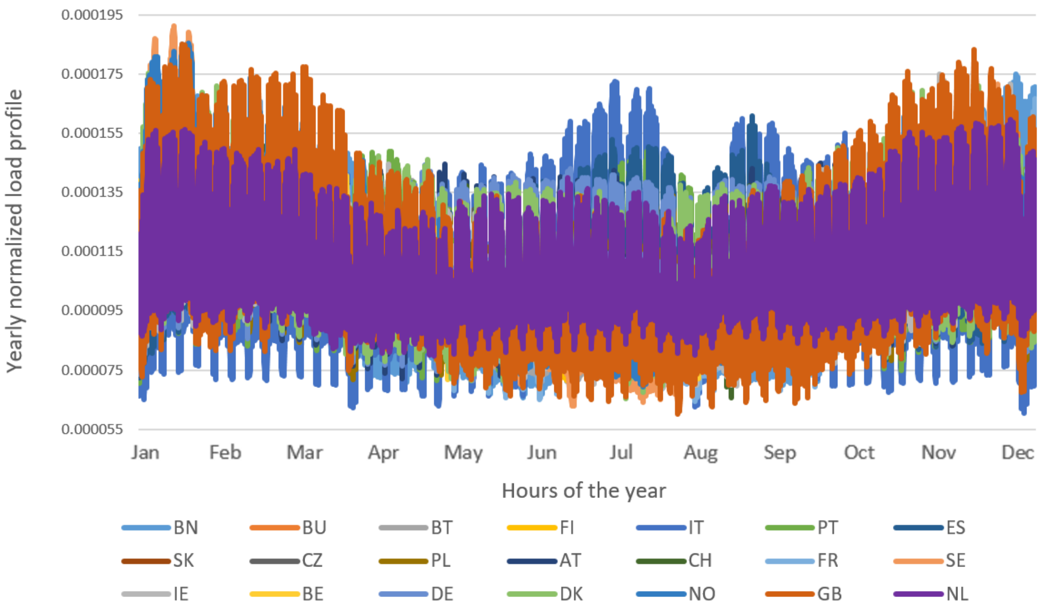


Figure 41, EU countries' yearly electricity load profiles. IESA-Opt assumes a high seasonal variability of load profile for northern countries. In addition, a weekly variation can be observed for all countries.

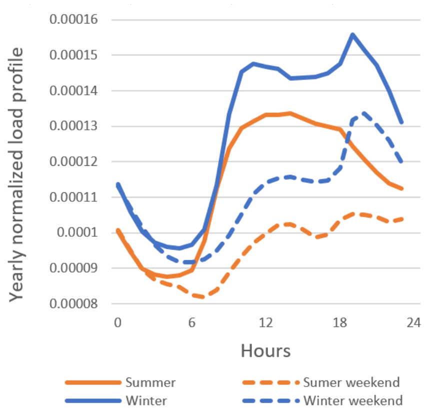


Figure 42, Electricity load profile of the Netherlands on a random weekday and weekend in summer and winter. Weekday loads have a relatively higher degree of daily variation compared to weekend loads.

The daily load profile can vary depending on the season and day of the week. Figure 42 shows the daily load profile of two random Thursdays and two random Sundays in winter and summer. In general, summer days have a lighter load compared to winter days.

Moreover, the load can have a second peak in winter days owing to the need for extra heating and lighting.

5.4. Method: Case descriptions

To explore the modeling trade-offs, we designed a set of cases in which we progressively enable specific capabilities applied to the reference scenario presented in Reference Scenario Section 5.3. The families of cases were named: A, for the cases in which we explore the granularity of the scope of the transition; B for cases exploring different representations of the EU power system; C, for cases exploring the enabling of diverse demand-side flexibility archetypes in the model; and D, for cases exploring the different levels of infrastructure representation.

The cases were generated to analyze the granularity level of the system configuration indicators. Therefore, the focus of this study is on relative results rather than absolute terms. Moreover, some cases represent hypothetical scenarios rather than practical scenarios.

5.4.1. **A Cases: Transitional scope**

To explore modeling capability, the reference scenario was run in IESA-Opt under four different cases that consider different transitional scopes. Each case varied the years considered for the transition. The first case (A1) determined the cost-optimal configuration for 2050; the second case (A2) did the same but for the years 2030 and 2050 simultaneously, where the remaining stocks from previous investments are still reflected in 2050; similarly, the third case (A3) did the same but for the years 2020, 2030, 2040, and 2050; and finally, the last case (A4) corresponded to the full deployment of the IESA-Opt capabilities, which covers the years between 2020 and 2050 at intervals of 5 years (7 periods in total). Case A3 was used as the reference case (R-A3) for family B and C cases, as it provided good results as an objective comparative framework and it required significantly less time than case A4. This means that all the following groups of cases (B, C, and D) consider the years 2020, 2030, 2040, and 2050 as the transitional scope.

5.4.2. **B Cases: European interconnection**

The impact of including European interconnectivity as a modeling capability was explored by progressively increasing the resolution of the interconnected European power system in five different cases. In the first case, B1, the national energy system was isolated as no European power system was represented in the case. In the second case, B2, the national energy system was connected to the European node, which had an average hourly electricity price (extracted from the reference scenario). The third case, B3, considered that all the demand and generation of EU regions were aggregated in one node that could trade electricity with the Netherlands. The next case, B4, provided a more detailed description of the EU power system by considering five interconnected regions (i.e., Belgium, Denmark, Germany, Great Britain, and Norway) as independent nodes. In the last case, R-A3, the resolution was increased to include 21 interconnected European nodes, as demonstrated in Figure 43.

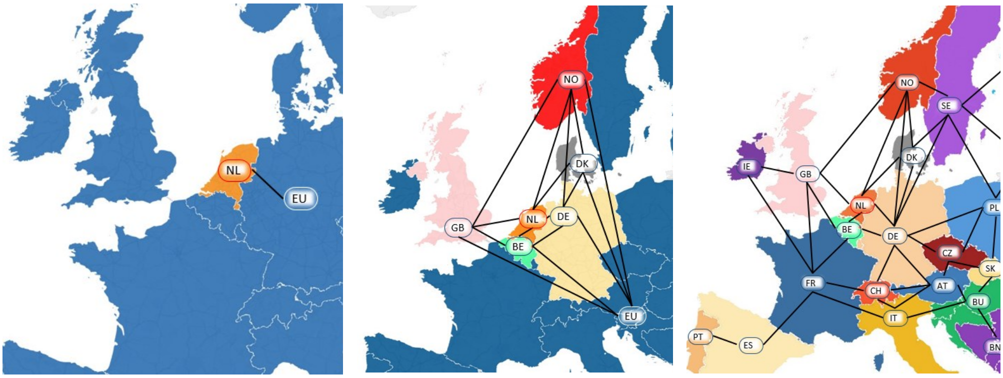


Figure 43, European interconnection representation in IESA-Opt; from left to right: Cases B3, B4, and R-A3.

5.4.3. **C Cases: Demand-side flexibility enhancements**

Demand-side flexibility in IESA-Opt was divided into seven major groups: flexible CHPs, shedding technologies, demand response, storage technologies, smart charging of electric vehicles, and vehicle-to-grid storage. Table 23 presents the list of technologies that were considered under each archetype for this chapter. To explore the impact of flexibility enhancements in the model, nine different cases were used: one where no flexibility was allowed to occur in model (C1), one that applied the full flexibility description of IESA-Opt (R-A3), and seven intermediate cases in which all forms of flexibility were allowed except for one: without flexible CHPs (C2), shedding technologies (C3), demand response (C4), storage technologies (C5), EV smart charging (C6), and vehicle-to-grid (C7). It is important to mention that further descriptions are still possible; for instance, more industrial activities could apply shedding, some other industrial activities could apply demand response to reschedule their production lines, residential demand response can be disaggregated in specific technologies, and more storage technologies could be analyzed. However, data availability is limited in this topic and the main objective was to test the capabilities of the different archetypes.

Archetype	Sector	Technology
Flexible CHPs	Waste	CHP from waste
		CHP from waste with CCUS
	Services	Mini CHP from gas
		CHP from gas
		CHP from hydrogen
	Industry	CHP from gas
		CHP from gas with CCUS
		CHP from solid biomass
		CHP from solid biomass with CCUS
		CHP from liquid biomass
		CHP from liquid biomass with CCUS
Shedding	Ammonia	Solid state ammonia synthesis
	Hydrogen	Alkaline electrolyzer
	Refineries	Methanol from electrolysis and DAC
		Methanol from electrolysis and external CO2
		Fischer Tropsch from electrolysis and DAC
		Fischer Tropsch from electrolysis and external CO2
Demand Response	Residential	Flexible residential demand
		Electric heat pumps with water storage tanks
Storage	Power	Compressed air aboveground storage
		Compressed air underground storage
	Heat Network	Hot water storage tank
Smart Charging	Cars	Electric vehicle with SC
	LDVs	Electric vehicle with SC
	HDVs	Electric vehicle with SC
Vehicle-to-grid	Cars	Electric vehicle with V2G

Table 23, Flexible technologies considered within each flexibility archetype.

5.4.4. **D Cases: Infrastructure representation**

IESA-Opt represents the infrastructure of certain commodity networks such as electricity, natural gas, hydrogen, district heating, and captured CO_2 (CCUS). The infrastructure representation imposed time-frame and distance constraints with certain costs in the form of transport lines (such as pipes and cables), transformers, and compressors to adjust to the required operational level of voltage or pressure of the lines. To measure the relevance of including such representations into the energy model, eight cases were designed in which the infrastructure capabilities of IESA-Opt were disabled. The first case disabled infrastructure representations of cables, pipelines, transformers, and compressors of electricity, gas, hydrogen, heat, and CCUS (D1). The second case disabled only the representation of transmission cables and voltage transformers for the transport of electricity (D2). The third and fourth cases ignored pipelines and compressors for the transport of natural gas (D3) and hydrogen (D4), respectively. The fifth and sixth cases ignored the presence of pipelines for district heating (D5) and CCUS (D6), respectively, as only one form of transport is used for their descriptions. Finally, the last case corresponded to the reference case in which all the infrastructure capabilities were enabled in the model (R-A3).

The resulting 25 cases used to explore the level of detail used to describe the four aforementioned modeling capabilities are summarized in Table 24. Different IEMs have different objectives and it is quite common for certain features to be sacrificed for more focus in other areas owing to the limited availability of computational resources. The intent behind testing the four capabilities in a range between the lack of their representation to the most detailed representation available in IESA-Opt was to determine if it was relevant to invest modeling resources to describe them. This could provide valuable guidance for modelers when deciding which capabilities could be sacrificed for the sake of their own modeling goals.

Transitional Scope	**European Interconnection**	**Flexibility Enhancements**	**Infrastructure Representation**
A1: - Cost-optimal configuration of year 2050. A2: - Simultaneous cost-optimal configuration of years 2030 and 2050. A3: - Simultaneous cost-optimal configuration of years 2020, 2030, 2040, and 2050. A4: - Simultaneous cost-optimal configuration of years 2020, 2025, 2030, 2035, 2040, 2045, and 2050.	B1: - No European interconnection at all. B2: - Simplified-single European interconnection with average EU electricity price. B3: - Single interconnection with a European node assuming copper plate among all surrounding countries. B4: - Connection with 5 interconnected countries surrounded by one large European node. R-A3: - Complete IESA-Opt EU power system representation with 20 surrounding nodes.	C1: - Without flexibility. C2: - Without CHP's flexibility. C3: - Without shedding of conversion technologies. C4: - Without demand response. C5: - Without storage technologies. C6: - Without EV's flexibility. C7: - Without vehicle-to-grid flexibility. R-A3: - All the flexibility forms considered in IESA-Opt.	D1: - Without any representation of infrastructure. D2: - Without electricity networks description. D3: - Without gas networks description. D4: - Without hydrogen networks description. D5: - Without CCUS networks description. D6: - Without district heating networks description. R-A3: - All the infrastructure represented in IESA-Opt.

Table 24. The summary of cases used to explore modeling capabilities.

5.5. Results

5.5.1. **Transitional scope**

The impact of the number of periods considered for the transition, according to cases A1, A2, A3, and A4, as introduced in 5.4.1 is illustrated in Figure 44. It is possible to observe that the number of considered periods strongly impacts the outcome of the system configuration.For instance, the system cost in 2050 increases by 9.5% as the considered transitional periods increase from 1 to 7 periods (A1 vs. A4). This is an expected result, as increasing the number of periods imposes an extra constraint to the problem which is derived from an intrinsic "inheritance" of the existing technological stock from previous years. The difference between 4 and 7 periods (i.e., cases A3 vs. A4) progressively increases with time until it reaches 4.2% for 2050. Furthermore, although less noticeable, the transitional scope also affects the 2050 shadow price of CO_2, as shown in Figure 44. The CO_2 price of cases A1 to A3 ranged between 1938 and 1956 €/ton of CO_2, while the price in A4 remained at in 1911 €/ton with a maximum difference of 2%. The shadow price for A4 was lower as it already presented a more expensive energy system, thus, if the targets are reduced by 1 ton of CO_2, the system has more "cheaper" options available in comparison to other cases.

The CO_2 price was extracted as the shadow price of the emission constraint, which is the marginal value of the objective function by emitting one extra unit of emissions (i.e., ton) in a certain year. Therefore, this parameter does not necessarily represent the price of CO_2 but rather the costs of marginal technologies to reduce CO_2 emissions. With stricter emissions targets, the shadow price increases further.

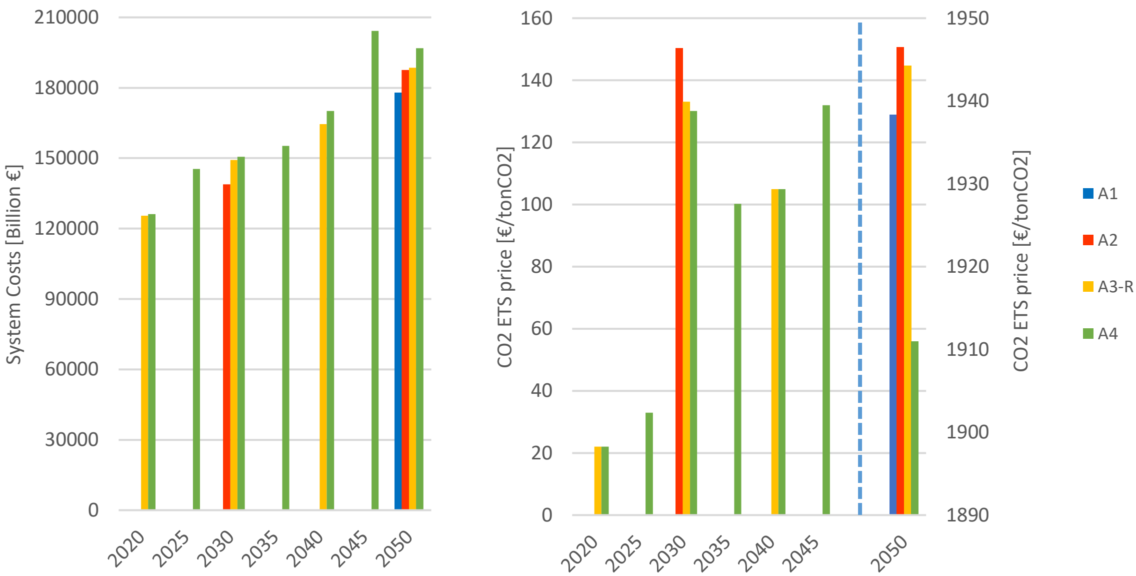


Figure 44, Left: comparison of the system costs at the different years of the transition for the 4 cases used to explore the transitional scope considerations of the model.
Right: comparison of CO2 ETS price between cases A1-A4. To better demonstrate differences in 2050, the results are reflected on the secondary right axis.

To explain the differences in costs, we looked at the sectoral cost composition of the four cases, as presented in Table 25. However, before explaining the differences, it is important to bear in mind that certain technologies become cheaper due to technological learning.

For instance, A4 needs to meet system requirements in previous years; therefore, sometimes the investment costs in previous years are more expensive than in 2050. As such, it does not necessarily mean that different costs represent substantially different system configurations but represent a reflection of the technology costs of the periods in which the investments were made. However, few conclusions can be extracted before considering sectoral configurations. For instance, it is evident that having more periods favors the adoption of district heating networks, as well as the role of hydrogen as an energy carrier.

	System Costs' change relative to A4 [%]			
Sector	**A1**	**A2**	**A3**	**A4 [B€]**
Residential	-26.0	2.0	-4.4	22.2
Services	-45.0	-35.6	-32.3	13.9
Agriculture	-7.9	-7.9	0.4	2.5
Industry	-8.2	18.6	3.2	10.6
Transport	-6.6	-6.6	-3.6	75.6
Power NL	3.7	-0.3	-1.6	42.3
Refineries	-31.1	-18.8	-19.4	2.0
Heat Network	-93.3	-74.7	-70.7	0.1
Final Gas	-34.1	-32.3	8.0	3.6
Hydrogen	-17.3	-24.2	-8.9	0.7
Fossil	0.5	3.0	3.9	17.8
Others	-17.6	-15.4	-13.9	1.8

Table 25, Sectoral decomposition of system costs' change for the four transition cases.

When we focused on configurational aspects, we found that although many of the technological configurations remain practically unchanged, there were notable differences as reported in Table 26. Most of the differences occurred in the transport sector and in the selection of heat technologies. For instance, in case A1, the model opted to use fuel motorcycles vs a predominant mix of electric motorcycles in A4; A1 adopted a 90/10 ratio of smart charging/vehicle-to-grid enhancements for passenger vehicles, while A4 opted for a 60/40 ratio; the ratio of electric to hydrogen buses is 1/3 in A1 versus 7/11 in A4; and A1 used only ICE ships, while A4 distributed the fleet almost evenly between ships using bunker, ICE, and CNG ships. In the residential sector, A4 substituted a tenth of the electric heat pumps with district heating as compared to A1; in the services sector, A1 adopted hybrid heat pumps while A4 went for the full electric heat pumps. In the industrial sector, the ratio of hybrid gas boilers with CCUS and hydrogen boilers was 2/9 and 4/9 for cases A1 and A4 to produce high-temperature heat, respectively. In the same sector, albeit for low-temperature heat, A1 opted for heat pumps while A4 selected geothermal heat. As a consequence, case A4 used 7.3% more electrolyzers to satisfy the hydrogen demand than A1. Finally, 11 Mton of CO_2 of the total emissions were allocated differently as well, where the ETS sectors further reduced their efforts by 2 Mton of CO_2 in A1 than in A4 to allow for more emissions in non-ETS sectors.

Activity	Technology	Units	A1	A4
Motorcycles	ICE Vehicle - Motorcycle	Gvkm	7.2	1.0
	Electric Battery Vehicle - Motorcycle	Gvkm	0.0	6.3
Passenger cars	Electric Battery Vehicle FLEX - Cars	Gvkm	36.0	24.1
	Electric Battery Vehicle P2G - Cars	Gvkm	3.7	15.4
Buses	Electric Battery Vehicle - Bus	Mvkm	162.6	254.0
	Hydrogen Fuel Cell Vehicle - Bus	Mvkm	488.0	396.6
International navigation	Heavy Oil Ship - International	Mvkm	0.0	58.1
	ICE Ship - International	Mvkm	146.3	38.8
	CNG Ship - International	Mvkm	0.0	49.5
Residential heating	District Heating - LT Heat for Houses A+	PJ	0.3	3.5
	Electric Heat Pump GW - LT Heat for Houses A+	PJ	33.8	30.5
Services heat	Hybrid Heat Pump - LT Heat for Services	PJ	85.9	0.0
	Electric Heat Pump Soil - LT Heat for Services	PJ	0.0	85.8
Industrial HT Heat	Hybrid Boiler Gas with CCUS - HT Heat for Industry	PJ	60.6	47.2
	Boiler H2 - HT Heat for Industry	PJ	14.3	28.4
Industrial LT Heat	Heat Pump Electricity - LT Heat for Industry	PJ	51.9	0.0
	Geothermal HP - LT Heat for Industry	PJ	0.0	46.8
Hydrogen	Alkaline Electrolyzer - Hydrogen Production	PJ	198.7	214.3
Emissions	ETS sectors	MtonCO_2	-18.3	-16.3
	non-ETS sectors	MtonCO_2	29.3	27.3

Table 26, Most significant differences in the use of technologies between cases A1 and A4

The electricity load will increase by almost three times from 340 PJ in 2020 to 1326 PJ in 2050, mainly due to the increase in the electrification rate. The main source to satisfy this substantial demand for the Netherlands will be the installed capacities of offshore wind turbines. In 2050, the electricity generation mix does not change considerably by changing the transitional scope. Electricity from solar PV remains an attractive option for the model due to technological learning and cost reductions until 2050. Moreover, the model nearly reaches the 90 GW installed wind offshore capacity, resulting in more than 760 PJ of electricity generated from mainly the North Sea region. The only major change is the reduction in imports in case A4, which can be explained by the reduction in the electricity load due to more accurate modeling assumptions (i.e., modeling the whole transition period).

Electricity mix in 2050 [PJ]	A1	A2	A3	A4
Co-fired Coal wCCS	1.4	1.4	1.4	1.3
CCGT	21.7	21.7	21.6	21.3
CCGT wCCS	15.4	15.4	15.3	15.3
GT	2.8	2.8	2.7	2.6
Biomass	5.6	5.5	5.1	5.3
Onshore Wind	57	56.8	56.8	57.2
Offshore Wind	766.9	767.8	766.5	762.3
Solar PV Fields	41	40.7	40.8	41.3
Industrial Solar PV	70	70	70	70
Residential Solar PV	84	84	84	84

Electricity mix in 2050 [PJ]	A1	A2	A3	A4
Hydro	0.9	0.9	0.9	1
Imports	418.2	417.9	421.5	374.6
Exports	56.1	56.9	58.5	59.5

Table 27, Electricity generation in PJ across cases A1 to A4. The overall generation mix does not change considerably.

We provide an overview of selected modeling elements to analyze the effect of the transitional capability in IESA-Opt in Table 28. From this, we can conclude that depending on the goals of the study, fewer transitional periods can be included to save computational time and resources at the expense of providing cost underestimations. The system configuration obtained by the simplified approaches differs only on a few activities and can predict CO_2 prices and system costs with underestimations of 10% or lower. However, it is important to mention that the underestimations provided by the simplifications are not only due to lifetime infeasibilities but also due to the higher effect that technological learning has on the solution when fewer periods are considered.

On the other hand, when discussing the requirements of including a more accurate representation of the transition in IESA-Opt, we can conclude that the modeling requirements are not as determinant as the computational needs. The model description does not differ depending on the number of periods considered (unless only the target year is modeled) and the data requirements also do not differ greatly (as technological learning is usually reported for the whole transition and not only for a year in particular). However, the scale of the problem can be significantly affected by the transitional choice, which might not only result in longer run times but also in the need for a larger RAM capacity and stronger CPU.

Case	Objective function	Memory needs	Run time	Data requirements	Model description
A1	Infeasibility[41]: 9.2%	13 GB	31 min	Cost and efficiency parameters of technologies for the target year only.	The transition formulation can be avoided.
A2	Infeasibility: 4.6%	28 GB	115 min	Cost and efficiency parameters for all the periods. The initial existing stock becomes more important as more periods are considered.	The transition formulation is required.
A3-R	Infeasibility: 3.7%	54 GB	271 min		
A4	-	89 GB	456 min		

Table 28, Overview of selected modeling elements around the transitional capability in IESA-Opt.

Furthermore, the transitional configuration of the model could be further strengthened by including more intermediate periods or by extending the scope of the transition further

[41] Underestimation of 2050 costs as compared with the case with the best representation available (A4)

from 2050. This would increase the computational demand, while also requiring the collection of data assumptions from beyond 2050, which are not easily available.

5.5.2. **European interconnection**

The European power system representation has a more noticeable effect on the modeling results. As noted in Figure 45, providing a dispatch representation with generation parameters (B3, B4, and B5) has a major impact on the system costs. For cases B1 and B2, where no EU interconnection and a simplistic average electricity trading price approach are used, respectively, it is possible to overestimate system costs. In addition, the abnormal difference in variable operation costs between case B1 and the others is due to the model reaching the most expensive supply option to meet the demand. This option does not satisfy the electricity demand, which leads to the assumed VOLL of 3000 €/MWh (we used the AEX price cap, although sometimes different values can be found in literature) to be a feasible alternative to reach decarbonization when external electricity is not available and when running more thermal units is not possible owing to the emissions constraint.

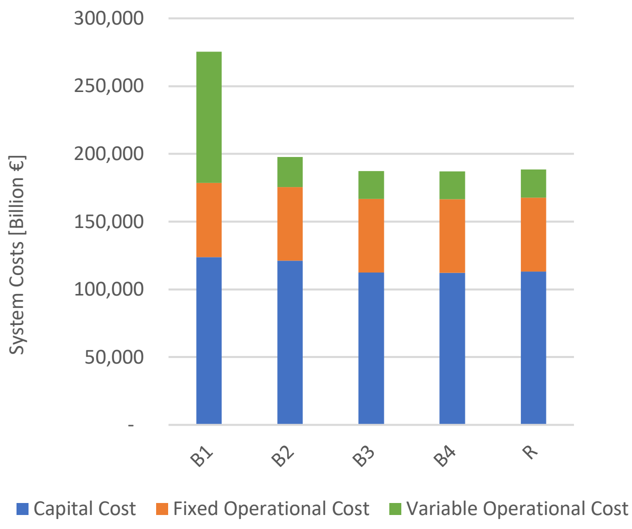


Figure 45, Comparison of the 2050 system costs for the 5 different cases used to explore the EU power system representation in IESA-Opt. System costs in case B1 are considerably higher.

To understand how deeply the power interconnection formulation can permeate to other sectors, we analyzed Table 29, which compares the 2050 sectoral costs for each of the cases. It is possible to observe that, other than for cases B1 and B2, costs differ very little for most sectors. The main exception to the latter is the hydrogen sector, where cases B3 and B4 underestimated sectoral costs by 12.3% and 17.8%, respectively. This happens as a less constrained EU power system allows the accommodation of more electricity for “conflictive hours” from outside the Netherlands. The latter results in the use of only 99 PJ of electrolyzers for cases B3 and B4, lower than the 136 PJ from the reference case. This cascades to lower infrastructural needs of only 8 and 7.43 GW networks for cases B3 and B4, respectively, as compared with R. Interestingly, the latter infrastructure needs are a consequence of the required capacities for hydrogen production of 199.5, 180.1, and 232.6 PJ for cases B3, B4 and R respectively, which evidences the amount of hydrogen production shedding in the cases. This analysis is a perfect example of the usefulness of having an IEM able to simultaneously consider flexibility at an hourly resolution coupled with an EU power system to identify and measure cross-sectoral feedbacks.

	System Costs’ change relative to R [%]				
Sector	**B1**	**B2**	**B3**	**B4**	**R [B€]**
Residential	-3.1	-2.8	-0.2	-0.1	21.2
Services	84.2	84.8	0.1	0.6	9.4
Agriculture	0.0	-6.4	1.5	-0.3	2.5
Industry	-0.3	-1.1	-0.1	0.0	10.9
Transport	0.5	0.2	-0.4	-0.4	72.9
Power NL	175.9	4.5	-1.9	-2.6	41.6
Refineries	-22.1	-26.6	-1.2	3.0	1.6
Heat Network	-31.8	-50.0	4.5	0.0	0.0
Final Gas	-12.5	-14.5	0.1	0.2	3.9
Hydrogen	-6.7	-9.1	-12.3	-17.8	0.6
Fossil	-4.1	-5.3	-0.2	-0.1	18.5
Others	41.6	30.0	-2.1	-1.7	1.5

Table 29, Sectoral decomposition of the change in system costs for the five EU interconnection cases

The behaviors of the import and export flows, which are greatly affected by the adopted EU representation, help to further visualize the differences. Figure 46 demonstrates that both import and export flows in B2 greatly differ from other cases; such differences tend to increase with time, mostly due to the price split that occurs as a consequence of VRES generation in the system. Additionally, the B3 formulation tends to underestimate the import and export flows even when the net difference of cases B4 and B5 is not substantial. This happens as a consequence of the European copper plate configuration, which diminishes the need for trading to alleviate both VRES excess and scarce hours. We can also notice that, up to 2040, the Netherlands evolves from a net importer to a net exporter of electricity during the transition due to the acceleration in VRES deployment in the upcoming two decades, a result which is in line with the Climate and Energy Outlook 2019 [184]. However, for the year 2050, this situation is completely reversed as a consequence of the relatively more aggressive decarbonization of the Netherlands Energy system considering other EU countries[42], where importing electricity is accounted for by the system as a clean source of relatively cheap electricity. This is a major consequence of having an IEM that can endogenously determine electricity imports and exports. A power system model cannot provide such insights as they do not account for the emissions of the whole energy system.

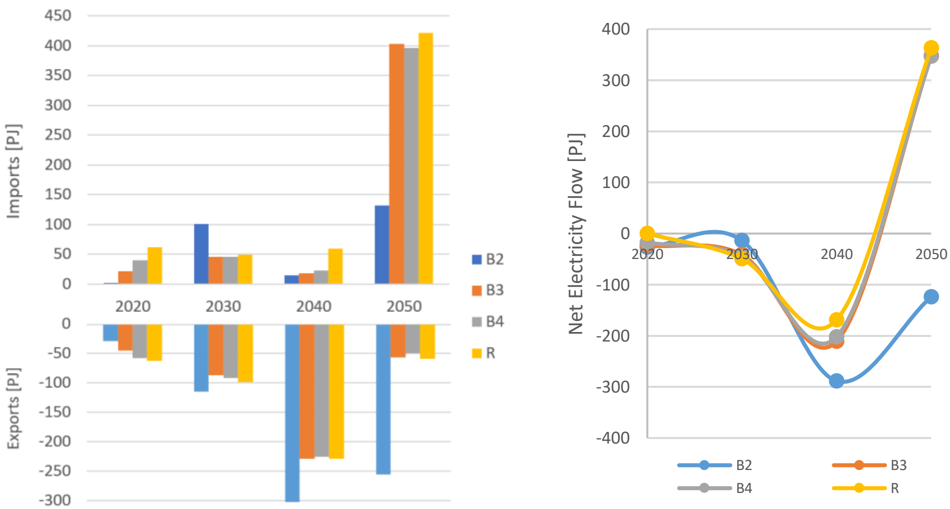


Figure 46, Comparison of the import and export flows to explore the EU power system representation in IESA-Opt. Left: The import and export level of each case compared to the reference case (i.e. R). Right: The net electricity flow compared to the reference case.

Furthermore, the level of detail in the EU power system description has a direct impact on electricity prices, electrification, and curtailment. The latter indicators extracted from each case are presented in Table 30. The amount of electricity used in 2050 tends to increase with an increase in the level of description, where case R presents a 3% higher electrification than cases B3 and B4, and over 20% higher than cases B1 and B2. In addition, the average prices of cases B3, B4, and R are considerably lower than those of cases B1 and B2, which is in line with the substantial gaps in most of the results obtained for both groups. The curtailment in case B1 was 20% higher than in the reference case, while the other three were lower by 49%, 4%, and 7% for cases B2, B3, and B4, respectively. Similarly, the price variabilities follow a similar pattern in which cases B3, B4, and R report similar values, and B1 and B2 significantly over- and underestimate variability, respectively. These observations not only reinforce the importance of

[42] Note that the assumptions surrounding the EU energy system evolution play a key role in this observation. For a complete description of the evolution of the EU generation assets for each IESA-Opt node assumed for this study, refer to the database of the Reference Scenario available online [151].

describing the generators in the EU power representation but also show that when the focus is the national energy system, acceptable results can be obtained with the simplifications proposed in B3 and B4.

Case	Average electricity price in 2050 [M€/PJ]	Average price variability in 2050 [M€/EJ-s]	Electricity use in 2050 [PJ]	Total curtailed electricity in 2050[43] [PJ]
B1	668.44	4.9	1,103.82	416.41
B2	109.44	1.2	1,134.33	178.34
B3	72.43	1.8	1,341.80	332.97
B4	72.50	1.8	1,344.22	324.18
R	76.97	1.8	1,380.46	347.44

Table 30, Comparison of key indicators for the integration of VRES into the system for the 5 different cases used to explore the EU power system representation in IESA-Opt.

As a final analysis of this topic, we show how the description of the EU interconnection impacts the adoption of flexible technologies. Figure 47 provides the 2050 operational volumes of each of the considered flexibility archetypes in IESA-Opt in the different cases. It is possible to see that the EU interconnection description has little to no impact on a few archetypes, namely CHP's flexibility and EV's smart charging, and a moderate impact on demand response. However, for shedding, storage, and V2G, it is crucial to include the representation of the European generators, as indicated by the differences between the results obtained by cases B1 and B2 with respect to cases B3, B4, and R. In the first group of cases, shedding seems to be significantly overestimated, while storage plays a minimal role and V2G is not even present. In the second group, shedding did not differ between the three cases but storage and V2G did; however, these differences never exceeded 20%. These results are in line with previous observations, highlighting the importance of the modeling description of the EU power generators, and showing that simplifications in cases B3 and B4 can yield similar results to the more complete representation presented in the reference case.

[43] The 2050 installed capacities of wind are 112, 112, 102.4, 104.3, and 104.4 GW for scenarios B1, B2, B3, B4, and R-A3, respectively.

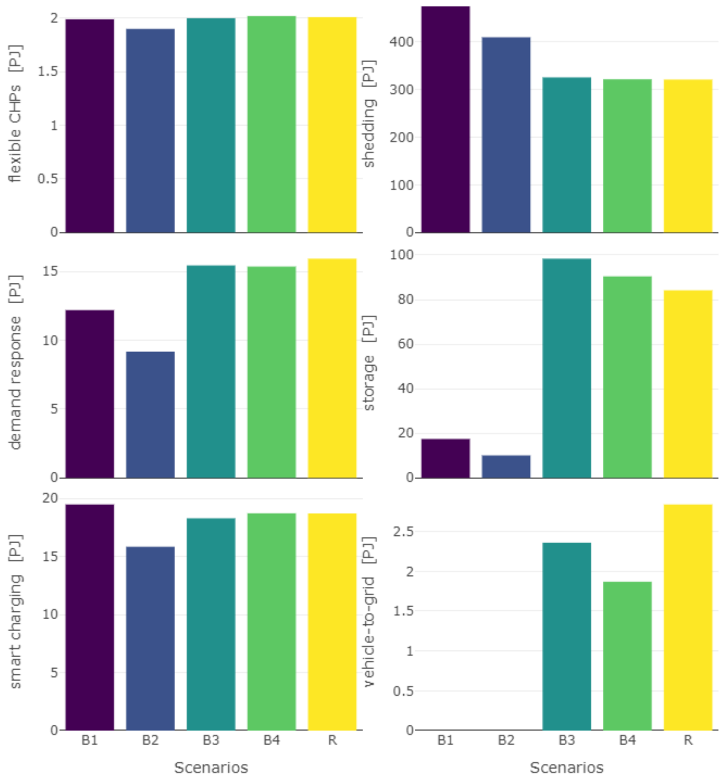


Figure 47, Comparison of flexibility volume applied in each of the archetypes considered in IESA-Opt in 2050. In each sub-plot, the R value represents the reference case. Values are expressed in PJ of electricity per year.

The electricity generation mix varies significantly across B cases. In case B1, Table 31 shows a substantial amount of undispatched electricity, which is the result of a system-wide phenomenon. The main reason is the lack of “clean” electricity, as there is no imported electricity and all clean electricity sources such as wind and solar reach the maximum installed capacity constraint. Moreover, producing electricity from fossil fuel sources results in CO_2 emissions, which needs to be highly constrained by 2050. Therefore, the system cannot serve electricity at certain hours of the year, resulting in 85.8 PJ of undispatched electricity. The same situation occurs in case B2. However, owing to the availability of the import and export flexibility options, the system can export when there is excess wind and import when wind and solar profiles are at their lowest levels.

In other B cases, as the model can optimally set the electricity price, it has a higher degree of import and export flexibility. This results in substantial (clean) electricity imports at any required hour of the year, which can be used in carbon capture processes such as the P2Liquid Fischer–Tropsch process. Therefore, there is more carbon budget available for fossil-based generators such as CCGT or CCGT wCCS.

Electricity mix [in PJ]	B1	B2	B3	B4	R
Co-fired Coal wCCS	0	0	1.8	1.7	1.4
CCGT	0	1.1	14.9	15.8	21.6
CCGT wCCS	0	0	9.4	10.1	15.3
GT	0	0	2.5	2.4	2.7
Biomass	0	0	5.6	5.3	5.1
Onshore Wind	58	57.3	56.6	56.6	56.8
Offshore Wind	790.6	774.3	756.6	756.7	766.5
Solar PV Fields	41.8	41.4	40.4	40.4	40.8
Industrial Solar PV	70	70	70	70	70
Residential Solar PV	84	84	84	84	84
Hydro	1	1	0.9	0.9	0.9
Imports	0	132.2	403.4	396.6	421.5
Exports	0	255.8	55.9	49.6	58.5
Undispatched Electricity (VOLL)	85.8	0	0	0	0

Table 31, Electricity generation mix changes significantly across B cases.

A comparison of the EU power system modeling approaches is presented in Table 32. Cases B1 and B2 overestimate system costs, while cases B3 and B4 underestimate them. However, except for case B1, these deviations are rather small, which does not necessarily mean that the solutions are good. The main interest in including a proper EU power system representation in a national model description is to correctly capture the effect that the import and export of electricity have on the operation of local supply and demand technologies. Thus, as the outcomes of cases B1 and B2 show, when the EU generators are not described as technologies with an independent (hourly) operation, the resulting system configurations differ considerably from the most detailed representation provided in the paper. Furthermore, when the independent operation of EU generators is considered, the results obtained are not strongly dependent on the number of nodes described. Nevertheless, a higher number of nodes might still provide additional insights when analyzing the role of interconnection lines with independent interconnected countries. Therefore, using fewer nodes is a viable alternative to reduce computational times (although not computational resources) while still correctly representing the national energy system configuration. It also further poses the advantages that less data must be collected and that fewer nodes must be represented in the model. However, the most extensive data requirement persists, as the total EU installed capacities for each technology are required.

Case	Objective function	Memory needs	Run time	Data requirements	Model description
B1	Sub-optimality: 45%	16 GB	66 min	Technology description of national generators	The EU power system description is omitted
B2	Sub-optimality: 3.7%	16 GB	70 min	B1 + average EU electricity prices prediction + interconnection potentials	An import and export technology
B3	Infeasibility: 1.1%	46 GB	114 min	B1 + EU generators data + EU installed capacity projections	For each extra country/node, a new activity (energy network)

B4	Infeasibility: 1.2%	48 GB	215 min	B3 + interconnection data with neighboring countries	is required, together with the description of all the technologies in the node. Note that the EU technologies also affect the objective function, so post processing modifications are required to extract national system costs
R	-	54 GB	271 min	B4 + interconnection data of all EU countries	

Table 32, Overview of selected modeling elements around the EU power system representation in IESA-Opt.

5.5.3. **Flexibility enhancements**

Perhaps the most meaningful results of this study are shown in Figure 48, where the 2050 system costs are shown for all eight cases in which IESA-Opt flexibility enhancements are explored. Here, it is possible to see that flexibility helps to decrease system costs of up to € 60.1 billion, or 24.2%, which is different between the case where no flexibility is present (C1) and where all flexibility forms are enabled (R). As mentioned, such a difference only appears for the year 2050, as before that, only 2040 shows a noticeable difference that does not exceed 3.5%. Another crucial observation is that only case C3 strongly diverges from others where only one form of flexibility is disabled; when shedding is not allowed system costs rise by € 29.4 billion (~11.8%). Similar observations can be made for the CO_2 shadow price[44], which rises from 1,944 to 8,099 €/tonCO_2 by disabling all forms of flexibility, and to 5,633 €/tonCO_2 when only shedding is disabled. Both arguments prove the importance of flexibility descriptions into integrated energy system analysis, as they can completely transform the resulting analysis. These results also highlight the role of shedding as a crucial flexibility archetype to include in the modeling approach. Finally, it is remarkable that the absence of most flexibility archetypes barely affects system outcomes. We can therefore conclude that most archetypes are comparable in their contribution to accommodate VRES in the system.

[44] It is relevant to mention that CO_2 shadow prices refer to the extra system costs required to further reduce emissions by 1 Mton of CO_2, and hence do not represent the average abatement cost of CO_2.

Figure 48, Comparison of system costs (left) and CO2 price (right) in 2050 with the reference case (i.e. R). Eight different cases are used to explore the flexibility enhancements in IESA-Opt. By only neglecting shedding flexibility options, system costs and emission prices increase drastically.

	System Costs' change relative to R [%]							
Sector	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**R [B€]**
Residential	-3.1	-0.2	-0.2	-3.8	-0.6	-0.3	-0.1	21.2
Services	87.8	44.3	56.2	0.8	0.0	0.5	0.0	9.4
Agriculture	-0.1	1.8	-1.0	-0.4	-4.1	-2.5	-0.3	2.5
Industry	-0.7	-0.2	-0.8	0.4	0.0	0.0	0.0	10.9
Transport	0.2	-0.3	1.7	0.2	2.4	1.1	-0.3	72.9
Power NL	110.2	0.2	46.5	1.2	-0.6	0.3	0.1	41.6
Refineries	-31.4	1.6	-29.7	-2.9	4.9	2.9	-1.1	1.6
Heat Network	-40.9	4.5	-36.4	295.5	31.8	4.5	13.6	0.0
Final Gas	-14.6	-4.4	-6.4	1.3	1.5	0.1	1.4	3.9
Hydrogen	-57.1	-2.9	-57.1	13.1	18.3	-1.0	2.9	0.6
Fossil	2.2	0.2	2.0	-0.6	-1.1	0.4	-0.2	18.5
Others	52.5	2.9	60.3	0.9	2.4	-0.2	0.3	1.5

Table 33, Sectoral decomposition of change in system costs for the eight flexibility cases

When analyzing the sectoral sources of the differences, we can identify four sectors in Table 33 where the main cost variations can be found: services, power, hydrogen, and heat networks. The increase in the power sector arises from the difficulties of the system to accommodate intermittent renewable sources when less cross-sectoral flexibility is available. In the case of hydrogen, when shedding is disabled, the system invests less in electrolyzers and when other flexibility forms are disabled, the system tries to compensate by investing more in hydrogen. The service sector uses CHPs for a long part of the transition and then substitutes this technology for hybrid or fully electric heat pumps.

Therefore, it is very sensitive to changes in the operation of CHP systems and the stability of electricity prices. The heat network seems to be very sensitive to disabling flexibility archetypes and shows a slight correlation with the amount of hydrogen produced, which is also used as a fuel for industrial heat in this sector.

The flexibility volumes were extracted for each of the cases, and their differences with the reference case are reported in Table 34. Here, we can observe that the volume of CHP flexibility is not strongly influenced by changes in other forms of flexibility other than slightly benefiting from the presence of shedding. Furthermore, other forms of flexibility remain unchanged when CHP flexibility is disabled. Similarly, the demand response also shows little effect on the disabling of other forms of flexibility, showing a moderate increase in operation when smart charging and shedding are disabled. In the transport sector flexibility, vehicle-to-grid plays an important substitutive role for the system, showing significant increments upon the disabling of the other archetypes (except CHPs). In addition, smart charging strongly benefits from the presence of storage in the system, and further develops when shedding and V2G are disabled. Finally, storage and shedding show the most pronounced effect on other forms of flexibility. When shedding is disabled, other forms of flexibility (except CHPs) increase their contribution substantially, and when storage is disabled, all other forms of flexibility decrease their contribution (except shedding).

		disabled archetypes per case					
		CHPs (C2)	Shedding (C3)	DR (C4)	Storage (C5)	SC (C7)	V2G (C8)
change in other archetypes [%]	CHPs	-100	-13.93	0.50	-2.99	0.00	0.50
	Shedding	1.20	-100	2.81	19.94	3.95	1.22
	DR	-0.63	15.12	-100	0.19	5.71	-1.19
	Storage	-0.05	42.79	3.80	-100	1.02	-0.12
	SC	-0.05	7.81	-3.53	-54.01	-100	6.74
	V2G	0.35	479.93	85.92	1343.31	357.75	-100

Table 34, Changes in the 2050 volumes of flexibility applied from the reference case to each case where a flexibility archetype is disabled.

Another relevant aspect to explore is the impact of disabling flexibility in electricity prices. A considerable difference is not present in price behaviors between the reference case and most cases, but cases C1, C3, and C5 present significant differences worth mentioning. To further explore the differences, the histograms of the electricity prices and price variability were extracted for cases C1, C3, C5, and R and are presented in Figure 49. Here, it is possible to see that when no flexibility is present in the system (C1), there is a large amount of extremely low and extremely high price events (roughly half of the total events). By applying all forms of flexibility, the extreme price events decrease to less than

15%, and price variability is significantly decreased. When shedding is disabled, C3, there is still a considerable number of extreme price events (roughly 33%), while the price variability histogram still significantly resembles the reference case with a slight decrease in extreme variability events. When storage is disabled, as in C5, the histograms still resemble that of the reference case, with the difference being a valley of low price events under 50 M€/PJ. From these observations, we can notice that shedding plays a key role in mitigating extreme price events and storage plays a key role in distributing the moderate price events more evenly. These results highlight the paramount importance of flexible demand in electricity dispatching.

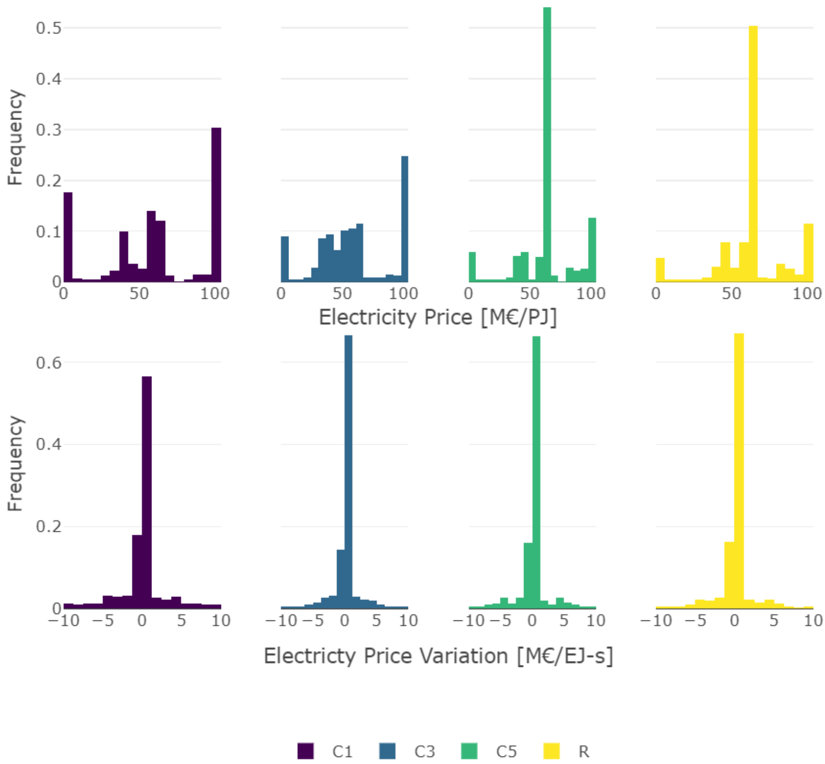


Figure 49, Comparison of the electricity price and variability histograms for cases C1, C3 and R.

The final observation of this section explores the interaction of flexibility enhancements with the import and export of electricity and the impact on system electrification and VRES curtailment. As shown in Table 35, similar results are extracted, where the absence of flexibility impacts the results severely by decreasing imports by 33% and increasing the amount of renewable electricity curtailed by 43%. For cases where flexibility enhancements are removed progressively, the absence of shedding (C3) and storage (C5) result in greater deviations from the reference case by increasing curtailed renewable electricity by 25% and 8%, respectively, and changes in the electricity exports of 43% and -

11%, respectively. Higher electrification is achieved when storage is disabled, followed by the disabling of demand response and CHP flexibility, while lower electrification occurs for cases C1 and C3, with substantial reductions of 8% for both cases. Disabling other flexibility forms resulted in a marginal impact on the reference case, except for a slight increase in curtailment of 5% when demand response is absent (C4). As a general observation, the presence of different forms of flexibility tend to have a low impact on electricity trading, except for shedding and storage, and contributes significantly to decreasing VRES curtailment.

Case	Import [PJ]	Export [PJ]	Electricity Use [PJ]	VRES Curtailment [PJ]
C1	281.2	61.9	1,273.2	498.6
C2	425.2	58.3	1,384.4	349.1
C3	302.2	82.2	1,271.1	433.4
C4	430.8	56.4	1,395.9	363.9
C5	434.2	51.8	1,418.5	374.3
C6	424.8	57.8	1,386.7	353.6
C7	421.4	58.1	1,380.2	348.3
R	421.5	58.5	1,380.4	347.5

Table 35, Comparison of key indicators for the integration of VRES into the system for the eight cases exploring flexibility enhancements in IESA-Opt.

The electricity mix in 2050 can change considerably depending on the consideration of different flexibility options (see Table 36). Neglecting flexibility options results in a drastic increase of 55.7 PJ in undispatched electricity compared to the reference case. This can be explained by the inter-sectoral interactions in the energy system. As there is no flexibility option, the supply and demand for electricity cannot deviate from a reference profile. Although there are import and export options, the system cannot compensate for all the missing generation with these. Moreover, the system cannot use shedding technologies, which drastically electrify the industry and reduce emissions. The lack of shedding technologies pushes the system to choose non-electrified substitutes to meet industrial demand. Therefore, the system is highly constrained in the carbon budget and cannot invest enough in fossil peak shaver generators such as gas turbines. A similar reasoning applies in case 3, in which the undispatched electricity is lower than C1 because other flexibility options can provide supply and demand flexibility to some extent. The absence of other flexibility archetypes does not considerably affect the generation mix.

It should be noted that the hourly wind and solar profiles remain the same for all cases. This results in very low electricity generation from wind and solar sources at certain hours of the year. In case of the lack of flexibility options, the system invests in extra peak load capacity, such as gas turbines, which are expensive and polluting.

Electricity mix [in PJ]	C1	C2	C3	C4	C5	C6	C7	R
Co-fired Coal wCCS	0	1.4	0	1.5	1.8	1.4	1.5	1.4
CCGT	47	21.6	36	21.6	21.5	21.4	21.4	21.6
CCGT wCCS	12.7	15.3	20	15.4	15.3	15.4	15.2	15.3
GT	0	2.6	0	3.3	3.3	3.1	2.7	2.7
Biomass	0	5.2	0	6.2	6.4	5.8	5	5.1
Onshore Wind	52.9	56.8	55.4	57	57	56.8	56.9	56.8
Offshore Wind	726.2	767	779.9	770.7	768.2	767.9	766.5	766.5
Solar PV Fields	30.4	40.8	38.3	41	41	40.8	40.9	40.8
Industrial Solar PV	70	70	70	70	70	70	70	70
Residential Solar PV	84	84	84	84	84	84	84	84
Hydro	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Imports	281.2	425.2	302.2	430.8	434.2	424.8	421.4	421.5
Exports	61.9	58.3	82.2	56.4	51.8	57.8	58.1	58.5
Undispatched Electricity (VOLL)	55.7	0	19.9	0	0.1	0	0	0

Table 36, Electricity generation in PJ across cases C1 to C7. The overall generation mix can change considerably by neglecting flexibility options. In particular, neglecting shedding flexibility technologies can drastically affect the generation mix.

Two main conclusions can be drawn from this experiment. First, representing operational flexibility outside the power dispatch is important for correctly accounting for technological options that can help to make the energy transition substantially more affordable. Second, shedding (mainly represented as electrolyzers for the hydrogen network and electrolyzers for ammonia production and refineries) is the key form of flexibility to include in the energy system representation. These conclusions are supported by all results presented in this section, as well as by the objective function value as presented in Table 37, and are in line with studies pointing towards shedding and shifting as the two more cost-effective options [185]. It can be observed that the absence of cross-sectoral flexibility representation often leads to sub-optimal solutions, leading to overestimations of transitional costs. However, such capabilities come at a high computational price, as they can together increase computational times up to 314%, albeit without the need for additional memory. Nevertheless, if swift solutions are needed and no specific sectoral transport analysis is required, we recommend skipping electric vehicle flexible capabilities, as they do not have a major influence on the results, and they require more time to solve owing to the strong impact of the variable available capacity inherent to their operational profiles.

Another sensible element of the cross-sectoral flexibility formulation relates to the availability of data. The IESA-Opt proposed formulation {cite the IESA-Opt paper after the revision} requires extra data representing the extent and duration for which the operation of flexible technologies is shed or delayed. These data are usually available or can be reliably inferred only for well-described technologies such as electrolyzers, batteries, storage tanks, electric vehicles, and some industrial processes. However, some other technologies such as generic demand response in the residential sector require assumptions or further technological disaggregation, which might result in either extra uncertainties or further model complexity. In particular, for IESA-Opt, it is recommended that special attention should be paid to these parameters when further developing the model.

Case	Objective function	Memory needs	Run time	Data requirements	Model description
C1	Sub-optimality: 31%	43 GB	86 min	No further data required	No flexibility description
C2	Sub-optimality: 1.6%	48 GB	168 min	All except CHPs operation zones	Each capability requires its own flexibility formulation accordingly with presented in the IESA-Opt paper {cite the IESA-Opt paper after the revision}
C3	Sub-optimality: 16%	48 GB	155 min	All except shedding capacity and non-negotiable loads	
C4	No difference	50 GB	205 min	All except share of flexible demand, and non-negotiable loads	
C5	Sub-optimality: 0.6%	51 GB	224 min	All except charging rates, storage capacities and efficiencies	
C6	Sub-optimality: 0.2%	50 GB	150 min	All except electric vehicles operation profiles, charging and storage capacities	
C7	No difference	50 GB	172 min	All except electric vehicles operation profiles, charging, storage capacity and efficiencies	
R	-	54 GB	270 min	All	All of the above

Table 37, Overview of selected modeling elements of the eight cross-sectoral flexibility cases in IESA-Opt.

5.5.4. **Infrastructure representation**

The impact of considering infrastructure technologies such as transmission lines, transformers, and compressors can be observed in Figure 50, where the system cost of 2050 is compared for the cases with different infrastructure forms considered. The first observation is that the representation of infrastructure can greatly affect system costs, particularly the capital component, as a difference of 10% can be observed between cases D1 and R. The second observation is that only the electricity and gas network representation affect system costs significantly, as the system results are 3.3% and 5.9% cheaper, respectively. The volume of development of hydrogen, district heating, and CCUS networks is considerably lower regarding gas and electricity, which in combination with the long economic lifetime of the infrastructure technologies, makes their impact on the total system costs of 2050 remain well below one billion euro per year.

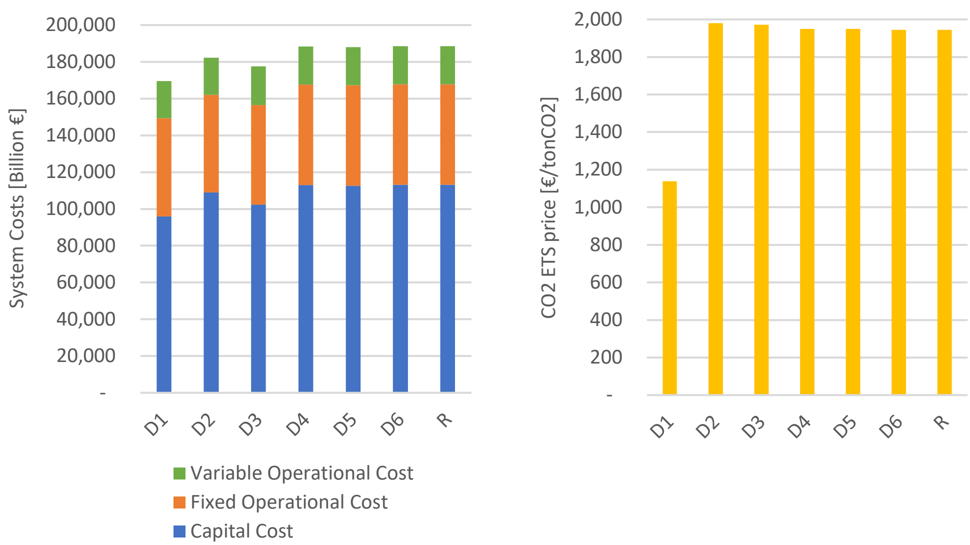


Figure 50, Comparison of the system costs (left) and CO2 piece (right) in 2050 for the seven cases used to explore the infrastructure representation in IESA-Opt. Assuming a freely connected energy network in case D1 can drastically reduce emission prices.

	System Costs' change relative to R [%]						
Sector	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**R [B€]**
Residential	-16.6	-0.1	-11.7	-0.1	-0.3	-0.3	21.2
Services	-29.9	0.6	-30.3	0.5	0.7	-0.4	9.4
Agriculture	-6.4	0.1	4.0	0.0	2.6	0.8	2.5
Industry	-24.3	1.4	-28.2	0.1	-2.4	-0.2	10.9
Transport	-0.2	0.2	-0.2	0.0	0.0	0.0	72.9
Power NL	-12.5	-14.3	-1.5	0.2	0.1	0.0	41.6
Refineries	-43.5	-19.7	7.2	-2.0	1.3	0.6	1.6
Heat Network	886.4	-4.5	531.8	4.5	18.2	131.8	0.0
Final Gas	-61.5	-1.0	-61.5	-0.4	0.5	0.8	3.9
Hydrogen	178.2	37.0	-8.9	-31.3	-0.7	-0.7	0.6
Fossil	-1.8	-2.1	3.1	-0.3	0.1	0.1	18.5
Others	-52.4	-3.5	-22.3	-0.1	-29.7	0.0	1.5

Table 38, Sectoral decomposition of system costs' change for the seven infrastructure cases

When evaluating the sectoral costs reported in Table 38, we found that cases D4, D5, D6, and R present almost no differences other than direct effects in their own sectors. On the other hand, cases D1, D2, and D3 present significant differences in costs. We can see that residential, service, and industrial sectors present considerably lower system costs, which is a consequence of adopting district heating and hydrogen technologies. In addition, the use of gas and electricity is 343 and 2556 PJ in D1 and 405 and 1869 PJ in D3, respectively, which, in contrast to the 325 and 1557 PJ, respectively, of the reference case, shows that omitting the complete infrastructure description might result in an overestimation of electrification, district heating, gas, and hydrogen as decarbonization activities.

As seen in Table 39, the most notorious case of feedback on other energy carrier infrastructure occurs in the absence of natural gas infrastructure description, where the required transformer capacities decrease owing to the higher flexibility provided to the system by under-constrained gas generators. However, this does not mean that the lack of infrastructure representation does not affect the system configuration in other sectors. An example of the latter is what happens in the production of synthetic fuels when the electricity infrastructure is not represented, as its absence decreases the amount of methanol produced from 188 to 153 PJ as the role of P2Liquid technology for avoiding network congestion events is no longer necessary. Similar examples are found in the volume of electrolyzers and district heating deployed in 2050, as the role of both technologies is greatly overestimated when no infrastructure representation is provided in the model.

Carrier	**Technology**	**Units**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**R**
Electricity	Transformer from LV to HV	GW	-	-	0.6	0.2	0.1	0.2	0.2
	Transformer from MV to HV	GW	-	-	4.4	5.0	5.2	5.1	5.1
	Transformer from HV to MV Baseload	GW	-	-	4.0	4.6	4.4	4.5	4.5
	Transformer from HV to MV Peaks	GW	-	-	9.0	9.5	9.4	9.4	9.4
	Transformer from LV to MV	GW	-	-	0.4	0.1	0.1	0.1	0.1
	Transformer from HV to LV	GW	-	-	8.3	7.8	7.9	7.9	7.8
	Transformer from MV to LV Peaks	GW	-	-	4.2	4.7	4.7	4.7	4.7
	HV Electricity grid cable	GW	-	-	39.9	39.9	40.1	39.9	39.9
	MV Electricity grid cable	GW	-	-	13.9	14.0	14.0	13.9	13.9
	LV Electricity grid cable	GW	-	-	13.9	13.9	13.9	13.9	13.9
Natural gas	HD to MD natural gas compressor	GW	-	46.1	-	46.7	46.6	46.7	46.7
	MD to LD natural gas compressor	GW	-	41.3	-	41.8	41.7	41.8	41.8
	Natural gas HD grid pipeline	GW	-	81.8	-	81.9	83.1	81.5	81.5
	Natural gas MD grid pipeline	GW	-	62.5	-	63.3	63.5	63.3	63.3
	Natural gas LD grid pipeline	GW	-	50.0	-	50.0	50.0	50.0	50.0
Hydrogen	HD to LD hydrogen compressor	GW	-	0.6	0.6	-	0.6	0.6	0.6
	Hydrogen HD grid pipeline	GW	-	1.8	1.5	-	1.4	1.5	1.5
	Hydrogen LD grid pipeline	GW	-	0.6	0.6	-	0.6	0.6	0.6
CCUS	CCUS grid pipeline	Mm	-	2.0	2.0	2.0	-	2.0	2.0
Heat	LT Heat network pipeline	Mm	-	0.7	0.7	0.7	0.7	-	0.7

Table 39, Installed capacities of infrastructure technologies in 2050 for the different cases.

The electricity generation mix can change drastically if the infrastructure constraints are neglected. In case D1, where the national transmission lines are considered as a copper plate, the model invests heavily (i.e., 97 GW) in offshore wind energy because the model does not need to invest in transmission lines between the offshore grid and the national grid. Moreover, there is no grid loss due to the copper plate assumption. Therefore, investing in offshore wind capacity becomes cheaper than importing electricity from neighboring countries, which includes grid losses and investment in transition lines over the imported electricity price. Table 40 shows that apart from case D1, the generation mix shows negligible differences across other D cases.

Electricity mix [in PJ]	D1	D2	D3	D4	D5	D6	R
Co-fired Coal wCCS	1.45	1.35	1.37	1.4	1.42	1.41	1.41
CCGT	19.86	20.57	20.41	21.43	21.57	21.59	21.59
CCGT wCCS	13.91	15.29	14.38	15.28	15.28	15.3	15.31
GT	1.75	2.32	2.26	2.64	2.63	2.66	2.66
Biomass	4.92	4.83	4.61	5	5.17	5.07	5.09
Onshore Wind	58.39	58.4	56.88	56.96	56.88	56.85	56.84
Offshore Wind	1195.68	767.89	766.21	767.56	767.9	767.1	766.53
Solar PV Fields	42	42	40.83	40.96	40.78	40.81	40.82
Industrial Solar PV	70	70	70	70	70	70	70
Residential Solar PV	84	84	84	84	84	84	84
Hydro	0.95	0.95	0.92	0.93	0.92	0.93	0.93
Imports	182.63	427.92	438.71	421.91	420.37	420.88	421.48
Exports	228.92	59.98	56.84	57.21	57.57	57.4	57.39

Table 40, Electricity generation in PJ across cases D1 to D6. The overall generation mix does not change considerably, except the considerable change in case D1 where infrastructure is neglected in the model.

As seen in Table 41, the main conclusion to be extracted from these experiments is that it is extremely important to correctly represent electricity and natural gas network infrastructure. When their representation is neglected, the results tend to underestimate system costs significantly and overestimate the role of key technologies such as electrolyzers. The other infrastructure representations (i.e., hydrogen, CCUS, and heat distribution networks) present a very limited effect in the system representation. The lack of representation of hydrogen and heat distribution networks results in a slight overestimation of the adoption of these technologies. On the other hand, the lack of a CCUS network description has little to no effect on the system outcome. Owing to the emission constraint being stringent, even when infrastructure costs are accounted for, the full potential of CO_2 storage and captured CO_2 reutilization are already reached. Therefore, if the computational time needs to be reduced, it is recommended to adopt an approach in which the infrastructure costs of the hydrogen, CCUS, and heat distribution networks are considered without describing the operational constraint imposed on the system, as this would reduce the problem complexity without considerably sacrificing solution quality.

Another aspect to consider is that representing infrastructure in a model requires an intricate data collection process, as many costs and operational parameters are spatially sensitive (i.e., a gas pipeline in a mountain range is more expensive than in a plain). IESA-Opt still has a large scope for improvement in this regard, as better data availability could enable the representation of intriguing transitional options such as industrial clusters for heat recirculation or district heating purposes, or even for hydrogen or CO_2 users.

However, even when this data is available at a sufficient quality, representing the role of these alternatives in the model to further decrease decarbonization costs would require a tailored formulation according to the specific designs of possible projects. This type of potential application can allow IEMs to be used as test fields for clustering and infrastructure design.

<table>
<thead>
<tr><th>Case</th><th>Objective function</th><th>Memory needs</th><th>Run time</th><th>Data requirements</th><th>Model description</th></tr>
</thead>
<tbody>
<tr><td>D1</td><td>Infeasibility: 10%</td><td>48 GB</td><td>161 min</td><td>No further data required</td><td>No flexibility description</td></tr>
<tr><td>D2</td><td>Infeasibility: 3.7%</td><td>51 GB</td><td>179 min</td><td>Electricity infrastructure and transformers costs, efficiencies and potentials</td><td rowspan="5">Each capability requires a supply and demand balance in the network for the considered dispatch resolution, as well as a maximum activity constrained by the infrastructure installed capacity. The complete formulation is presented in the IESA-Opt paper {cite the IESA-Opt paper after the revision}</td></tr>
<tr><td>D3</td><td>Infeasibility: 5.8%</td><td>50 GB</td><td>174 min</td><td>Gas infrastructure and compressors costs and potentials</td></tr>
<tr><td>D4</td><td>No difference</td><td>51 GB</td><td>231 min</td><td>Hydrogen infrastructure and compressors costs and potentials</td></tr>
<tr><td>D5</td><td>Infeasibility: 0.3%</td><td>50 GB</td><td>189 min</td><td>CCUS network infrastructure costs and potentials</td></tr>
<tr><td>D6</td><td>No difference</td><td>50 GB</td><td>220 min</td><td>Heat network infrastructure costs and potentials</td></tr>
<tr><td>R</td><td>-</td><td>54 GB</td><td>270 min</td><td>All of the above</td><td>All of the above</td></tr>
</tbody>
</table>

Table 41, Overview of selected modeling elements of the infrastructure representation in IESA-Opt.

5.5.5. **Computational resources**

It is logical to infer that by enabling a larger set of capabilities into the model, both solving time and computational affordability[45] are further compromised, both of which are crucial aspects when expanding problem analysis. To discuss the latter impact of the cases explored in this study, we report the computational times, memory requirements, and the resulting problem size (after pre-solving) for all the cases in Table 42.

For the family of A cases, the memory requirements and problem size seem to grow linearly with the introduction of each period, as indicated by the computational times. However, the last observation might be biased by the size of the RAM used as the number of hard-faults increased with larger problems, which made the calculation slower.

For the family of B cases, the complexity of the problem is not correlated with the problem size, as the problem sizes of B1 and B2, as well as those of B3 and B4, do not

[45] By computational affordability, we refer to the ability to solve a computational problem without the need for out-of-norm processors or memories.

differ greatly. However, as expected, the computational times increase with the complexity of the capabilities included in the cases. From the family of B cases, it is worth highlighting case B3, which yields suitable results at a national level and can run considerably faster than cases B4 and R. Next, for the family of C cases, it is highly noticeable that, by disabling flexibility, the problem becomes smaller and solves faster. One can perceive that the three flexibility enhancements with the most computational requirements are Shedding, V-to-G, and Smart Charging, while storage and demand response have the lowest impact on computational times. A similar observation can be extracted for D cases, where disabling infrastructure representation decreases problem size and solving times. For these cases, gas and electricity infrastructures impose the highest burden on the solution, while hydrogen and district heating infrastructure affect the problem size and times the least.

Finally, it is important to mention that IESA-Opt's mathematical problem is formulated in AIMMS [148]. It is solved with the Gurobi 9.01 solver via the barrier method using a laptop with 32 GB of RAM and an Intel i8750-H processor. It should be noted that we used an average laptop to perform the analysis. However, with the aid of more powerful hardware, the computational times can be further reduced, especially for larger problems. This could allow the further expansion of the problem or the use of multiple runs to perform sensitivity analyses under practical timeframes.

Case	Time [min]	# Variables [1e6]	# Constraints [1e6]	# Non-zeros [1e6]	Memory [GB]
A1	30.9	2.1	3.4	16.1	13.0
A2	114.6	4.9	7.3	34.7	27.5
R-A3	270.7	10.2	14.7	69.1	53.5
A4	456	18.5	26.1	125.2	88.2
B1	65.7	4.5	2.6	29.2	16.0
B2	69.2	4.5	2.7	29.5	16.0
B3	113.7	9.5	12.0	63.7	45.9
B4	214.7	9.7	13.2	66.1	47.7
C1	85.9	7.3	13.1	53.5	43.1
C2	167.5	8.9	14.1	61.9	48.2
C3	155.3	9.7	14.5	66.8	48.3
C4	205.4	10.1	14.6	68.0	50.1
C5	224.2	9.9	14.5	67.8	50.5
C6	150	9.8	14.4	66.8	49.7
C7	172	10.1	14.6	68.3	50.2
D1	160.6	9.7	14.5	62.6	48.4
D2	179	10.1	14.7	64.6	51.4
D3	173.6	10.2	14.7	68.6	50.3
D4	231.4	10.2	14.7	69.1	51.0
D5	189.3	10.2	14.7	68.8	50.3
D6	220.6	10.2	14.7	69.0	50.4

Table 42, Computational requirements of the mathematical problems resulting from the formulation of the different cases explored.

5.6. Discussion

Twenty-one cases were presented in this study to analyze the effect of the level of granularity in four modeling capabilities on several system configuration indicators. The main takeaways can be summarized as follows:

Transitional Scope

We can conclude that considering the goals of the study, fewer transitional periods can be included to save computational time and resources at the expense of providing cost underestimations (i.e., infeasibilities). This simplification does not affect the system costs and CO_2 prices considerably. Moreover, it reduces the computational load, resulting in much shorter run times and the reduced need for a costly computer. However, the model description and data requirements do not differ considerably by changing the number of periods considered. The transitional scope of the model could be extended further than in 2050. This would increase the computational demand while requiring the collection of data assumptions for beyond 2050, which is not easily available.

European interconnection

The main need to include an EU power system representation in a national model is for correctly capturing the effect of the import and export of electricity on the operation of local supply and demand. By considering the independent operation of EU generators, the main system indicators do not change significantly with the number of described nodes. Therefore, as long as a dispatchable European node is considered, using fewer nodes is a practical alternative to reduce computational loads while leading to minor deviations in the results from the full node representation. Moreover, it has the advantage that fewer nodal data need to be collected.

Flexibility enhancements

Representing operational flexibility outside the power dispatch is important for correctly accounting for technological options that can make the energy transition substantially more affordable. Moreover, shedding was identified as the key form of flexibility for cases with a high share of intermittent renewables. The presence of different forms of flexibility tends to significantly decrease the curtailment of intermittent renewables and has a low impact on electricity trading, except for shedding and storage. Moreover, the absence of cross-sectoral flexibility representation often leads to sub-optimal solutions, resulting in overestimations of transitional costs. Additionally, if electric vehicle analysis is not considered, we can neglect their flexibility as it requires substantial computational resources while having no significant influence on the system-wide results. Although flexibility data for well-described technologies are usually available, some other technologies such as the generic demand response in the residential sector require assumptions or further technological disaggregation, which result in uncertainties or further model complexity.

Infrastructure representation

By avoiding the representation of the electricity and natural gas network infrastructure, the results tend to underestimate system costs significantly and overestimate the role of key technologies such as electrolyzers. Other infrastructure representations, namely, hydrogen and carbon capture, utilization, and storage (CCUS), as well as heat distribution networks, have a very limited effect on the system representation. However, the lack of representation of the hydrogen and heat distribution networks results in slight overestimations in the adoption of these technologies. The lack of a CCUS network description has a negligible effect on the system outcome because the emission constraint is so stringent that the full potential of CO_2 storage and captured CO_2 reutilization are already considered. Therefore, to reduce computational time, it is recommended to consider the infrastructure costs of the hydrogen, CCUS, and heat distribution networks without describing the operational constraints imposed on the system.

Representing infrastructure parameters requires an intricate data collection process, as many of the cost and operational parameters are spatially sensitive. Energy system models can further improve in this aspect as better data availability could enable the representation of transitional options such as heat recirculation in industrial clusters, district heating, hydrogen, or CO_2 consumers. However, even when this data would be available at a required quality, representing the role of these alternatives would require a tailored formulation according to the specific goals of the project.

Computational load

The memory requirements and problem size seem to grow linearly with higher granularities in the transitional scope, similarly with the computational times. Moreover, the three flexibility enhancements with the most computational requirements were identified as shedding, vehicle-to-grid, and smart charging, while storage and demand response had the lowest impact on computational times. Furthermore, the representation of gas and electricity infrastructure imposes the highest burden on the solution, while hydrogen and district heating infrastructure affect the problem size and times the least.

The computational time of a mathematical problem can be reduced by either hardware or software improvements. To include higher details while maintaining low solving times, the hardware can be improved, as we used a relatively affordable laptop for this study. On the other hand, we presented several model-specific methods for improving computational times, while using a state-of-the-art solver configuration. These model-specific methods come with their own set of trade-offs, as explained earlier. It is recommended for modelers to set the computational expectations of the model based on the focus of the study.

5.7. Conclusion

In this chapter, we quantified some modeling trade-offs by employing an applied energy system model that covers all energy sectors, includes grid infrastructure, and integrates a transnational linear power system representation that includes cross-border trade. We generated 21 cases based on a reference scenario of the Netherlands as a case study, while the results can be interpreted for other similar national energy systems. We measured the cost of increasing resolution in each modeling capability in terms of computational time and energy system modeling indicators, notably, system costs, emission prices, electricity generation, and import and export levels.

Our findings can be summarized as: First, reducing the transitional scope from seven to two periods can reduce the computational time by 75% while underestimating the objective function by only 4.6%. Second, if the electricity trade with each neighboring country is not the focus of the study, modelers can assume a single EU node that dispatches electricity at an aggregated level (while still describing the distribution of the technologies taking part in the dispatch). This assumption underestimates the objective function by 1% while halving the computational time. Furthermore, shedding technologies (such as electrolyzers) and storage options are a must for any integrated energy system with high shares of variable renewable energy, as their absence can strongly affect modeling outcomes in terms of the objective function, system configuration, and operation of technologies. In general, neglecting flexibility options can drastically decrease the computational time but can increase the sub-optimality by up to 31%. Finally, while reducing the computational time to half, the lack of electricity and gas infrastructure representation can underestimate the objective function by 4% and 6%, respectively.

This study comes with some shortcomings. For instance, we assumed flat profile for a considerable number of technology options, while hourly load profiles can play an important role in determining the optimal portfolio of technologies. Acquiring hourly load profiles for each technology and energy source (e.g., wind and sun) can be a challenge. Therefore, modelers may assume the same profile for a set of technologies, or use clustering methods in data preprocessing. It is highly suggested to analyze the impact of input data resolution on modeling results and computational loads.

This chapter can guide energy system modelers to better frame their modeling assumptions based on the focus of their study. The quantified modeling trade-offs presented in this chapter, can be used by other energy system modelers to better identify crucial computational gaps. Moreover, energy modelers can realize the quantified importance of analyzed modelling capabilities on accuracy of final results.

Analyzing the techno-economic role of nuclear power in the Dutch net-zero energy system transition [46]

Abstract

To analyze the role of nuclear power in an integrated energy system, we used the IESA-Opt-N cost minimization model focusing on four key themes: system-wide impacts of nuclear power, uncertain technological costs, flexible generation, and cross-border electricity trade. We demonstrate that the LCOE alone should not be used to demonstrate the economic feasibility of a power generation technology. For instance, under the default techno-economic assumptions, particularly the 5% discount rate and exogenous electricity trade potentials, it is cost-optimal for the Netherlands to invest in 9.6 GWe nuclear capacity by 2050. However, its LCOE is 34 €/MWh higher than offshore wind. Moreover, we found that nuclear power investments can reduce demand for variable renewable energy sources in the short term and higher energy independence (i.e., lower imports of natural gas, biomass, and electricity) in the long term. Furthermore, investing in nuclear power can reduce the mitigation costs of the Dutch energy system by 1.6% and 6.2% in 2040 and 2050, and 25% lower national CO_2 prices by 2050. However, this cost reduction is not significant given the odds of higher nuclear financing costs and longer construction times. In addition, with 3% interest rate value (e.g., EU taxonomy support), even high cost nuclear (10 B€/GW) can be cost-effective in the Netherlands. In conclusion, under the specific assumptions of this study, nuclear power can play a complementary role (in parallel to the wind and solar power) in supporting the Dutch energy transition from the sole techno-economic point of view.

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6.1. Introduction

A recent report by the IEA suggests a massive deployment of all available low carbon energy technologies to reach globally net-zero emission by 2050 [186]. As one of the low-carbon sources of electricity, nuclear can provide an essential contribution to the energy transition. As a result, it is expected that nuclear power will maintain its 10% share of the electricity generation mix globally by 2050 [186], which implies a growth in nuclear power generation as the electrification rate increases globally. China, India, and Africa are expected to account for a significant share of this growth, while developed economies in the US and Europe are expected to extend the operating lifetime of existing nuclear plants to meet decarbonization targets [187].

Several studies analyzed the role of nuclear power in the long-term energy transition. However, each comes with methodology gaps that affect the results and discussion on this role.

In studies based on power system models (PSM), the role of nuclear power in long-term energy planning was analyzed. For instance, the REX model was used for Sweden to minimize the cost of a future low-carbon electricity system without nuclear power [188]. The PLEXOS model of the European power system demonstrates that a fully renewable and non-nuclear European power system is feasible by 2050 at the expense of higher costs [189]. A TIMES electricity model study estimates 30-70% higher electricity supply costs in alternative low-carbon electricity pathways in Switzerland and its neighboring countries under a nuclear phase-out scenario [190]. Another study used detailed power system and nuclear power plant operation models to investigate the benefits of nuclear flexibility in the Southwest United States [191]. Some other studies used stochastic [192] and life cycle programming [193] methods in power system models to analyze the role of small modular reactors (SMR). Although these PSMs described the power system in detail and (some) accounted for cross-border electricity trade, they did not include all sectors and activities related to the decarbonization targets. Moreover, these PSMs could hardly optimize the endogenous demand-side flexibility supply options such as electric vehicles, heat pumps, and electrolyzers. While PSMs require specifying the power sector's emission cap as an exogenous scenario parameter, energy system models (ESMs) optimally distribute the emission reduction burden between all sectors. The same logic applies to the sectoral availability of sensitive resources such as biomass and CO_2 storage.

Several studies at the national geographical scale represented nuclear power in the energy system models: Although the impact of Finnish nuclear power on demand response was modeled using the EnergyPLAN model [194], the study did not analyze the cost implications of nuclear power. Using the TIMES model, a study investigated the reliability of the French energy system by 2050 [195]. Nevertheless, it does not consider the uncertainty of the nuclear costs in the analyses. Moreover, a study investigates the long-term energy transition strategies of South Korea, including nuclear power using the LEAP model [196]; however, the variability of nuclear power costs and its system implications were not evaluated. Furthermore, several scenarios for Great Britain's power system were investigated using the Calliope energy system model [197]; yet, the cost uncertainties of nuclear were not the focus of the study. Additionally, by applying the LEAP-OSeMOSYS model, the role of nuclear power in several Spanish energy scenarios is analyzed [198] without considering its cost variations. Even though these studies analyze the role of nuclear power in the electricity generation mix, they do not focus on the implications of nuclear power on the energy system.

Since the Netherlands is used as the case study, we review, in addition, the recent Dutch reports that focus on the role of nuclear power in the energy system:

A recent Dutch study, the Berenschot and Kalavasta report (2020), found that nuclear energy is more expensive than renewables, except when nuclear power always takes precedence over the electricity grid, and the government takes on a large part of the financial risks [199]. The role of the social discount rate is thoroughly analyzed for the economic feasibility of nuclear power. However, the study only analyzes the target year 2050 without considering the transition pathway, which can lead to underestimating the resulting system costs by neglecting the system's decommissioning costs, existing stock, and inertia [8].

The ENCO report (2020) claims that nuclear could play an essential complementary role in the Dutch decarbonization pathway by complementing variable renewable energy sources (VRES) [200]. However, the conclusions are based on the plant-level Levelized Cost of Energy (LCOE) calculations rather than system-wide LCOE calculations. Consequently, the calculated LCOEs do not correctly reflect the cost of system-wide constraints such as flexibility supply investments, operational constraints, cross-border electricity trade, and infrastructure limitations. Additionally, the ENCO report is criticized with four major drawbacks [19]: assuming high solar and wind costs, ignoring the merit-order curve, deviating from Dutch energy policies, and the absence of system-wide analyses.

The KPMG report (2021) follows a different approach in which it presents interviews with nuclear market parties to identify how nuclear energy can be realized as cost-effective as possible and what governmental interventions are required [201]. This study provides suggestions to the government on several aspects of nuclear power, such as technological choices, financing options, governmental intervention, decommissioning, waste treatment, and optimal location. Nevertheless, this study does not analyze the techno-economic role of nuclear power in an integrated energy system model.

The TNO report (2022) concludes that nuclear power can play a complementary role with sun and wind to satisfy high electricity demands in long-term [202]. This TNO report used the OPERA optimization model [203], which uses time-slices in comparison with hourly temporal resolution.

Table 43. Summary of reviewed studies and the corresponding knowledge gaps.

Model or Method	Case study	Knowledge gap / Shortcoming	Source
REX	Sweden	No endogenous power demand	[188]
PLEXOS	Europe	No endogenous power demand	[189]
TIMES	Switzerland	No endogenous power demand	[190]
UC/ED	United States	No endogenous power demand	[191]
EnergyPLAN	Finland	Not analyzing the uncertainty of nuclear costs	[194]
TIMES	France	Not analyzing the uncertainty of nuclear costs	[195]
LEAP	South Korea	Not analyzing the uncertainty of nuclear costs	[196]
Calliope	Great Britain	Not analyzing the uncertainty of nuclear costs	[197]
LEAP-OSeMOSYS	Spain	Not analyzing the uncertainty of nuclear costs	[198]
ETM	Netherlands	Neglecting the transition by simulating only 2050	[199]
LCOE analyses	Netherlands	No system-wide LCOE calculation	[200]
Stakeholder interview	Netherlands	No quantitative techno-economic analyses	[201]
OPERA	Netherlands	No hourly temporal resolution	[202]

Table 43 summarizes the reviewed studies' major methodological shortcomings and knowledge as follows: (1) The system-wide implications of nuclear power in a transition to a net-zero energy system is barely discussed. These implications refer to not only economic feasibility of this technology, but also its impact on other energy sectors, system costs, and flexibility demand and supply. Therefore, integrated energy modeling tools are required to compute the system-wide influence of techno-economic decisions [5]. (2) Moreover, there is a great controversy on the cost data of nuclear and VRES. The range of cost data for these technologies is relatively wide [6], which can significantly affect the cost-optimal power generation mix. (3) Furthermore, small modular reactors (SMR) as flexible nuclear technologies are not included in the reviewed studies. However, they are expected to play an active role in providing flexibility to the power system [7]. (4) Finally, neglecting cross-border electricity trade can overestimate electricity prices by 40% [8]. Moreover, it can significantly affect the optimal electricity import and export levels—subsequently, the power generation mix. Therefore, assumptions regarding the cross-border electricity trade can highly affect the investment and operation of nuclear power.

We address the four knowledge gaps mentioned above using the highly detailed energy system model, IESA-Opt-N. This model is an improvement to its older version, IESA-Opt. This model optimizes investments of the energy system over the horizon from 2020 to 2060 in 5-year time steps while simultaneously accounting for hourly and daily operational constraints.

The primary contribution of this study can be summarized as "investigating the techno-economic role of nuclear power in a national energy system, considering the current inertia of the energy system and the flexibility requirements identified by hourly operation modeling". This study is framed around four themes, corresponding to the four knowledge gaps (Figure 51): (1) system-wide impact of nuclear power in an integrated energy system, (2) the role of nuclear cost uncertainties on cost-effective nuclear investment decisions, (3) the role of SMR nuclear power as a flexible generation option on cost-effective nuclear investment decisions, and (4) impact of the cross-border electricity trade on economical nuclear investment decisions.

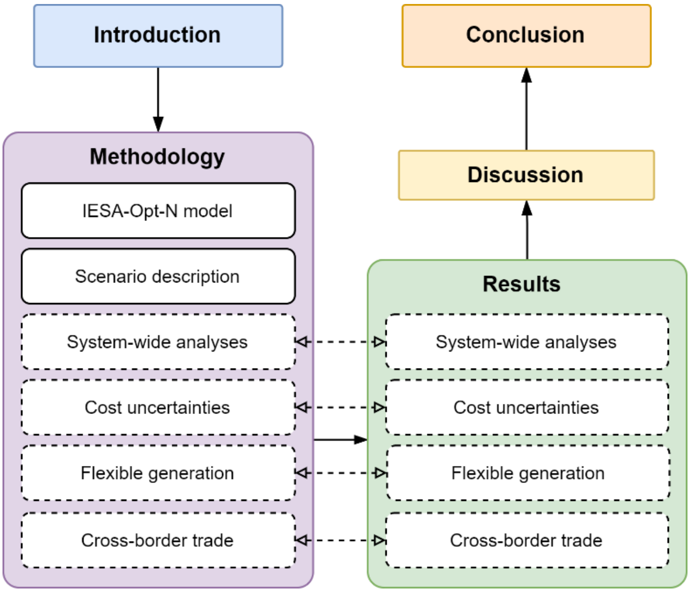

Figure 51. Structure of this study. The methodology behind the analyses on four themes of this study is described in the methodology section, while the results are presented in the results section.

We primarily focus on the techno-economic role of nuclear power. However, this technology faces several other challenges that are not discussed in this study: energy security and independence ([204], [205]), social acceptance ([206], [207]), and radioactive waste management ([208], [209]).

6.2. Method

This section describes the model used and the improvements we made to the model. Next, we briefly describe the main scenarios used in this study: the reference and nuclear scenarios. Afterward, we use the scenario simulation and comparison approach to identify the role of nuclear on key system indicators in four themes: system-wide costs, sensitive technological costs, flexible generation, and cross-border trade.

6.2.1. **Modifying the IESA-Opt model to make IESA-Opt-N**

We use the IESA-Opt model implemented for the Netherlands to capture system-wide effects. This is a detailed open-source optimization ESM at the national level [210]. IESA-Opt models investments of the energy system over the horizon from 2020 to 2050 in 5-year time steps while simultaneously accounting for hourly and daily operational constraints. The model's objective function minimizes the net present value of energy system costs to achieve total energy needs under certain techno-economic and policy constraints (e.g., a specific greenhouse gas (GHG) reduction target in a particular year). It is an open-source and flexible model that can be used for other regions or countries (e.g., the North Sea region [211]).

In the IESA-Opt model, the operation of the electricity sector of the Netherlands and other EU countries (including Norway and Switzerland) is balanced hourly. Since the model's scope is at the national level, power sector investments occur only in the Netherlands. At the same time, the power capacity mix of EU nodes is fixed as exogenous scenario parameters.

The energy infrastructure is modeled in ten networks for different voltage levels of electricity, and different pressures of natural gas, hydrogen, and single carbon capture, utilization, and storage (CCUS) and heat networks. The gaseous networks are balanced daily due to their relatively low intraday variation [210].

The IESA-Opt model reflects the emission constraints of the EU Emission Trading System (ETS), the non-ETS sectors, and the international navigation and aviation sectors. Since ETS sector emissions are traded in the EU ETS market, we assume an exogenous ETS emission price projection as a scenario parameter. Because the national emission reduction policy targets both ETS and non-ETS sectors, we set the aggregate national emission constraint on both sectors. If the constraint is binding, the model generates an aggregated national emission shadow price, equal to the marginal increase in the system cost if the aggregated emission constraint gets one unit tighter.

Although IESA-Opt comes with several capabilities, it has some limitations. Therefore, this study modifies the model in two directions: objective function definition and cross-border electricity trade. The modified model is IESA-Opt-N, which stands for Integrated Energy System Analyses – Optimization – National.

Objective function definition

There are two mainstream ways of dealing with multi-horizon investments in the energy system models: (1) assuming a full overnight cost at the time of investment and a salvage value at the end of horizon (e.g., OSeMOSYS [212]). (2) distributing annualized cost over the lifetime of the technology after the first investment (e.g., Balmorel [213]).

However, the IESA-Opt model's objective function is formulated slightly differently. It refers to the system's net present value resulting from the set of decision variables confirmed by annualized investments, decommissioning, retrofitting, and use of technologies. Although this objective function annualizes the investments, it does not account for the annualized cost of technology stock in periods after the investment period. Therefore, the system tends to make more significant investments in earlier periods as it does not pay for the annualized capital cost of those investments in successive periods.

Therefore, we modify the objective function by adding the investment matrix before the capital component to represent total system costs (Equation 1). The binary investment matrix determines the presence of a technology option in each period based on its economic lifetime.

Moreover, we add a social discount factor (SDF) to weigh different periods and account for the net present value of costs (similar to the PyPSA-Eur model [214]). This discount factor (see Equation 2) is based on the assumed exogenous social discount rate that describes how society values future investments. The social discount rate should not be confused with the capital discount rate. The capital discount rate or Weighted Average Cost of Capital (WACC) is used to annualize the overnight capital investment costs. Although WACC can be different for each technology, we assume a 5% rate for all technologies in the reference scenario. Thus, with the addition of the social discount rate, the new objective function calculates the sum of the net present value of energy transition costs:

$$Objective\ Function_{IESA-Opt-N}:$$
$$\sum_{t,p}(1+r_s)^{p_b-p}\left(IM_{t,p,p^*}\left(i_{t,p}IC_{t,p}+s_{t,p}FOC_{t,p}+u_{t,p}VOC_{t,p}\right)\right) \qquad Eq. 1$$

Where:

$r_s = social\ discount\ rate$
$p_b = base\ period$

$i_{t,p}IC_{t,p} = annualzied\ investment\ costs\ \left(IC_{t,p}\right)\ of\ investments\ \left(i_{t,p}\right)$
$s_{t,p}FC_{t,p} =\ fixed\ operational\ and\ maintenance\ costs\ \left(FC_{t,p}\right)\ of\ the\ technological\ stock\ \left(s_{t,p}\right)$
$u_{t,p}VC_{t,p}$
$=\ variable\ operational\ and\ maintenance\ costs\ \left(VC_{t,p}\right)\ due\ to\ the\ use\ of\ the\ technologies\ \left(u_{t,p}\right)$

IM_{t,p,p^*}
$= the\ binary\ investment\ matrix\text{:}\ the\ presence\ of\ technology\ (t)\ that\ is\ in\ the\ system\ from\ period\ p^*$
$if\ \left(p^* \leq p \leq p^* + eco_{L_t}\right)\ then\ IM_{t,p,p^*} = 1\ else\ \ IM_{t,p,p^*} = 0$
$eco_{L_t} = economic\ lifetime\ of\ a\ technology\ (t)$

With the new objective function formulation, the capital cost of technologies is accounted for during their economic lifetime. However, the investments in the last modeling period may be distorted as the benefits of investments after this period are neglected. Since 2050 is crucial in current policies, we do not want these so-called end-of-horizon effects in 2050. Although this effect is already reduced by using annualized investment costs, we add two more periods (i.e., 2055 and 2060) to the model's horizon to further reduce this effect [215]. Since the additional periods aim to represent investment costs better, all energy system definitions, including activity levels and technological costs and potentials, are kept equal to their value in 2050.

Cross-border electricity trade

The IESA-Opt model optimizes the hourly operation of the electricity sector of the Netherlands and other EU countries (including Norway and Switzerland). This requires the evolution of EU generators and interconnection capacities as input to the model. These exogenous values were obtained from the Ten Year Network Development Plan of ENTSO-E [165]. However, the range for capacities is relatively high across different scenarios. Moreover, the power generation plan of each EU member state can vary significantly in time as it is strongly tied to political agendas. Therefore, we decided to decouple these uncertainties from the IESA-Opt model by removing the EU capacities.

The IESA-Opt-N model can use the cross-border electricity trade profile as an exogenous input. This profile determines the hourly availability and price of electricity at each period. Furthermore, the profile can get imported from other power system models (e.g., COMPETES[216] and PyPSA-Eur[217]). This method has two main advantages compared to IESA-Opt: first, the impact of the EU power system on the national system is quantified and measurable, and second, the computational load is lower, and thus the run-times are significantly quicker. However, it comes with one primary disadvantage: the inconsistency between the assumptions of national energy system and international power system models.

The electricity import and export prices and availability profiles vary depending on the underlying assumptions of the Netherlands and its neighboring countries' scenarios. Since the profiles can vary in many directions (i.e., hourly prices multiplied by hourly availabilities), performing a sensitivity analysis is complex. Moreover, measuring the impact of profile variations on national power generation decisions can be problematic. Therefore, we use a flat price to import and export electricity in this study. Moreover, we set a maximum import and export quota for each year. Thus, the model can decide how much to trade at each hour of the period, considering the total trade volume is less than the assigned quota for that period.

In summary, the modifications improve the solution's accuracy considerably (mainly by improving the objective function definition) while increasing the solution's stability and reducing the solving times substantially. Figure 52 demonstrates the visual methodological framework of the IESA-Opt-N model.

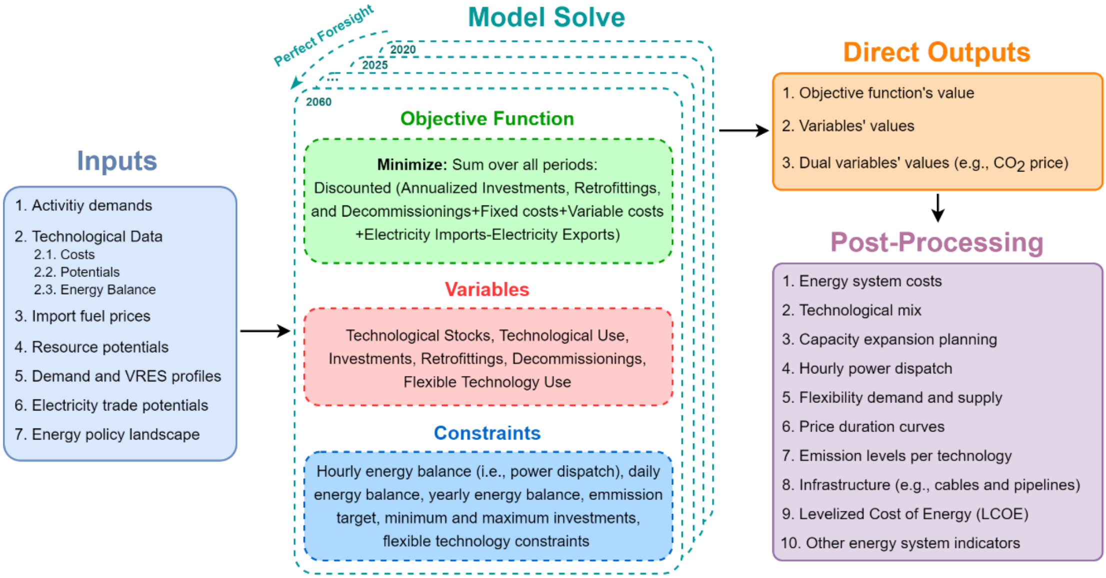

Figure 52. The methodological framework of the IESA-Opt-N model

6.2.2. **Reference and nuclear scenarios of IESA-Opt-N**

Here we provide a brief description of the reference scenario of the IESA-Opt-N model.

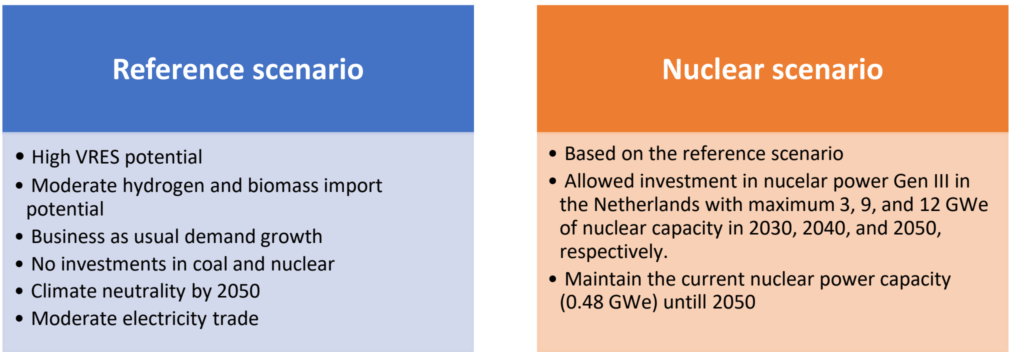

Figure 53. The summary of the reference and nuclear scenarios

Sanchéz et al. provide a complete description of the required input data and scenario definition elements for the IESA-Opt model [210] that is similar to IESA-Opt-N scenario assumption elements. The reference scenario used for this chapter aims for a carbon-neutral energy system in 2050 by employing high shares of VRES, biomass, and hydrogen. Figure 53 summarizes the fundamental assumptions of the reference and nuclear scenarios. The rest of this section describes these two scenarios further in detail. First, we describe the main elements of the reference scenario definition, such as demand drivers, fuel and resource costs, technology and resource potentials, technological costs, and emission constraints. Then, we define the nuclear scenario by describing its significant changes compared to the reference scenario.

Reference scenario

The environmental policy landscape of the Netherlands follows the EU Green Deal [218], where the Netherlands steps up its ambition to reduce its greenhouse gas (GHG) emissions by 55% compared to 1990 levels in 2030 [219], and becomes GHG neutral in 2050 [220].

The projected development of activities and part of the resource costs are extracted from JRC's POTEnCIA central scenario for the Netherlands [154], which is based on GDP growth rates presented in the 2018 aging report [155]. This scenario leans towards business-as-usual economic development, which would fall within the second shared socioeconomic pathway (SSP2) [156]. In addition, the costs of biomass were extracted from the reference storyline of the ENSPRESO database [157], as well as most of the considered potentials for renewable technologies in the Netherlands.

The reference scenario uses data from central scenario descriptions of different sources. Most of the technologies described in IESA-Opt-N are based on the reference scenario of the ENSYSI model [28], where low-carbon technologies experience a learning rate of at most 20%. Technology data projections of the transport sector are obtained from the POTEnCIA central scenario [154]. In addition, data projections for technologies such as P2Liquid alternatives, electrolyzers, and direct-air-capture units are obtained from TNO's technology factsheets [163].

The reference scenario assumes a moderate public-private interest rate of 5% for all technologies, including nuclear power. Since this rate is an essential factor in determining the economic feasibility of nuclear power, we perform sensitivity analyses on this parameter, explained in Section 6.2.4.

The complete technology data assumptions, as well as the link to the sources, can be found in the online portal of the model [151].

Renewable and nuclear generation costs and constraints

IESA-Opt-N defines technological costs utilizing Capital Expenditures (CAPEX), Fixed Operational and Maintenance (FOM), and Variable Operational and Maintenance (VOM) cost parameters. These cost parameters are imported from various sources listed in Table 44. CAPEX costs are affected by exogenous learning rates, and only their value in 2050 is presented here. The cost reduction parameter indicates the assumed average cost reduction every five years.

For nuclear power generation, the CAPEX represents the Overnight Construction Costs (OCC), consisting of civil and structural costs, major equipment costs, the balance of plant costs, electrical, instrumentation, and control supply and installation costs, indirect project costs, development costs, and interconnection costs. Generation III (gen III) nuclear costs are obtained from the MIT Nuclear technology study [6]. We assume a linear cost reduction in CAPEX from 7.2 billion € (B€)/GW in 2020 to 6 B€/GW in 2050. The FOM costs are estimated to decrease linearly from 0.16 B€/GW-year in 2020 to 0.13 B€/GW-year in 2050 [221]. Although the decommissioning and waste management costs are estimated to be 15% of the OCC [222], we consider these costs part of the VOM costs. The European Commission report assumes that the decommissioning cost is 0.49 M€/PJ, and waste management cost is estimated at 0.81 M€/PJ [223]. Obtaining the 3.13 M€/PJ variable costs from the MIT report [6], the total VOM is assumed 4.43 M€/PJ in all periods.

Small modular reactors (SMR) generally have less than 300 MWe capacity, and their "modular" feature makes it possible for a single reactor to be grouped with other modules to form a larger nuclear power plant [224]. SMR technology based on generation III reactors can get lifted to technology readiness level (TRL) 9 in approximately one decade, making it a feasible technological option from 2040 onwards [225]. The OCC estimate of SMRs ranges from 4241 to 6703 M€/GW [226]. Also, the CAPEX of SMR nuclear is estimated to be 30% higher than Gen III due to its lower technological readiness [227]. However, in the reference scenario, we assume a linear CAPEX reduction from 7.4 B€/GW in 2020 to 6.72 B€/GW in 2050 [228]. Moreover, we assume the same FOM and VOM costs as the nuclear gen III.

The economic lifetime determines the expected profitability duration of the investment. The technology will be decommissioned and removed from the system at the end of this lifetime. The capacity factor determines the maximum theoretical output of the technology compared to its maximum capacity. Wind and solar capacity factors are obtained from the IEA Net Zero report [186].

Nuclear power plants (NPPs) are usually deployed to supply base-load power. However, NPPs can reduce power output (i.e., through flexible generation or load-following) under certain physic-induced constraints. Among the most limiting constraints is the negative reactivity insertion following every reactor power drop due to the increased concentration of xenon, a strong neutron poison [229]. In practice, countries with large nuclear power shares (France) and high intermittent renewables (Germany), need NPPs to operate load-following [230]. Although lowering the power output can reduce NPP's revenues (as it does not significantly reduce generating costs), literature has showed that NPP's load-following can be profitable from social welfare perspective (i.e., such as baseload units' operation, renewables' integration, system operators' balancing, and consumer's price [230]).

However, in this study, we assume nuclear gen III to operate as base-load (i.e., non-flexible) and SMRs to operate as load-following (i.e., flexible generation). In this way, we can demonstrate the impact of nuclear generation flexibility (on several levels) on its economic feasibility (section 6.2.5). To account for the inflexibility of nuclear gen III generators, we assume a near-zero ramping rate, which is the rate of increase or decrease in the generated power per hour.

The only techno-economic difference between SMR and gen III nuclear in our database is the CAPEX and ramping values. Therefore, to avoid mixing the effect of these two parameters on the feasibility of this technology, we exclude this technology in the reference and nuclear scenarios. Instead, we perform a sensitivity analysis that is described in section 6.2.5.

Table 44. Assumed VRES and nuclear technological costs and constraints in 2050 in the reference scenario.
** estimated zero (i.e., 0.1). Since IESA-Opt-N uses an LP formulation, it does not solve unit-commitment problems that require MILP formulation. Sources: [114], [186], [231]*

Technology	CAPEX [B€/GW]	FOM [B€/GW-y]	VOM [M€/PJ]	Economic Lifetime [y]	Capacity Factor [%]	Ramping [%]
Wind offshore	1.51	0.047	0.1	20	60	100
Wind onshore	1.08	0.017	0.4	20	30	100
Solar fields	0.28	0.002	0.1	20	9	100
Nuclear Gen III	6	0.13	4.43	60	90	0.1*

Electricity trade potential

Electricity trade can play an essential role in determining the cost-effective nuclear investment capacity. However, the outlook of electricity trade volume and prices in 2040 and 2050 is somewhat uncertain. Therefore, we assume a subjective “moderate” electricity trade volume and price projection for the reference and nuclear scenarios (Table 45). The Netherlands imported 22.4 TWh and exported 19.8 TWh of electricity in 2020. We assume an increase in the electricity trade volume from 28 TWh in 2030 to 44 TWh in 2050. Furthermore, the assumed average import price increases from 58 €/TWh in 2030 to 115 €/MWh in 2050. Since this assumption can affect the results considerably, we do a sensitivity analysis on it under the fourth theme.

However, we assume a considerably lower export price. The model can optimally distribute the hourly electricity export with perfect foresight. This assumption is far from reality as the exports increase with an excess of VRES generation, while the neighboring countries also experience this excess. Therefore, we penalize the export price in 2050 (compared to the import price) by 36 €/MWh.

The hourly trade profile is optimized endogenously by the model depending on the national power demand, generation, and cross-border interconnection capacity.

Table 45. Assumed projection of electricity trade volume and prices.

Electricity trade	Units	Periods		
		2030	**2040**	**2050**
Import (or export) volume per year	[TWh]	28	33	44
Import price	[€/MWh]	58	86	115
Export price	[€/MWh]	22	50	79

Nuclear scenario definition

The nuclear scenario is based on the reference scenario with changes in nuclear investment constraints. The capacity expansion in the Netherlands is maximized at a subjective value of 9 and 12 GWe in 2040 and 2050, respectively (Table 46). Moreover, the lifetime of the current nuclear power plant with 0.484 GW capacity is extended for 20 years (i.e., until 2053). Since this scenario focuses on the economic feasibility of nuclear power, we only allow for nuclear gen III investments by constraining nuclear SMR. Therefore, the feasibility of nuclear SMR is analyzed separately in the SMR and flexible generation theme.

Table 46. The assumed nuclear capacity expansion constraints in the nuclear scenario

Maximum nuclear capacity (Netherlands)	Units	Periods		
		2030	**2040**	**2050**
Nuclear gen III	[GW]	0.48	9.48	12.48
Nuclear SMR	[GW]	0	0	0

6.2.3. Theme one: analyzing system-wide costs

Due to the increase in cross-sectoral energy flows, analyzing a particular technological decision (i.e., investment or operational decision) is rather complex. For instance, the investment decision on wind turbine capacity depends on the hourly electricity demand in other sectors (i.e., electrification rate) and the available flexibility in the system to handle peak hours. However, these variables depend on other demand drivers and other technologies' available potential and cost. Therefore, we require an integrated energy system model to account for the system-wide impacts of certain decisions. To provide further details on the cost flow of the energy transition, the IESA-Opt-N model reports several cost indicators: system costs, mitigation costs, sectoral costs, final energy prices, and LCOEs. Afterward, we describe the flexibility definition and available flexibility options in IESA-Opt-N.

System costs

The model's objective function is to minimize the net present value of all costs stemming from the investment and operational decisions in the national energy system. The system can also incur negative costs (i.e., revenues) by exporting energy. The system costs indicator is divided into four categories: CAPEX, FOM, VOM, and trading costs. The first three elements are obtained by summing up the corresponding cost elements of available technological options. Trading costs are the net balance of import costs and export revenues of electricity, gas, and oil-based products based on hourly and daily energy carrier prices.

To provide more insights into the system costs, also mitigation costs, sectoral costs, average final energy prices, and LCOEs are presented.

Mitigation costs

Although the system costs indicator shows the evolution of all cost components of the energy system, it can be misleading in comparing scenarios. A high share of the system costs depends on the level of energy activity demand drivers, irrespective of environmental targets. Although the system costs can vary under different environmental targets, the inertia of this high share can underestimate the change in the system costs.

Therefore, we use the mitigation costs indicator to report the system costs of reducing greenhouse gas emissions. We calculate the mitigation costs as the system costs difference in a specific scenario with and without emission reduction targets. For instance, to measure the mitigation costs of this study's reference scenario, we first calculate the reference scenario’s system costs (including the climate targets by 2030 and 2050). Afterward, we set the maximum allowed carbon emission equal to 1990 levels; then, we recalculate the costs. Finally, we report the difference as the mitigation costs of the reference scenario.

$$Mitigation\ Costs_{scenario\ X} = System\ Costs_{scenario\ X} - System\ Costs_{scenario\ X^*}$$

$$scenario\ X^* = scenario\ X\ with\ maximum\ carbon\ budget\ equal\ to\ 1990\ levels$$

Although this method increases the computational run times of the model (as each scenario needs to be optimized two times), it provides a clear and transparent cost indicator for scenario comparison.

Sectoral costs

Sectoral costs explicitly account for all costs related to the energy technologies in each sector, including the fuel prices paid by each sector based on the market perspective of the energy costs. Therefore, the total sum of sectoral costs will be higher than the system costs as the marginal cost of energy carriers is higher than the average energy costs. Moreover, the sectoral costs include the trading component for the sectors involved in energy trade (e.g., power generation sector). In addition, the infrastructure cost components of each sector are explicitly reported.

Average final energy price

The average final energy price is equal to the weighted average price of each final energy carrier considering its hourly or daily marginal price variations. Therefore, this parameter can be used as a valuable indicator to compare the affordability of the energy for final consumers in different scenarios.

LCOEs

LCOE measures the average net present cost of energy generation for a generating plant over its lifetime. IESA-Opt-N reports both the theoretical and realized LCOEs. The theoretical LCOE is calculated based on the theoretically generated energy resulting from the exogenous capacity factor. Alternatively, the realized LCOE is calculated based on the generated energy from solving the optimization problem. The added value compared to similar LCOE based studies (that only calculate theoretical LCOEs, e.g. [15]) is that the current study uses an ESM to calculate the realized LCOEs. This accounts for indirect system-wide costs, such as infrastructure or flexibility costs, to balance the power system.

Flexibility supply sources in IESA-Opt-N

Flexibility refers to the ability of the energy system to respond to the variability and uncertainty of the residual power load (i.e., power load minus VRES generation) within the limits of the electricity grid [232]. When the share of intermittent renewables increases, the demand for flexibility in the energy system grows; thus, energy sectors are required to become more interconnected through conversion (e.g., Power to X) and storage technologies.

Flexibility can be measured either in ramping (GW/h), energy (GWh), or capacity units (GW). In this study, we measure the flexibility in energy and capacity units. Based on its direction, flexibility demand can be caused by either upward or downward residual load. We define flexibility in energy units as the surface area under the duration curve of the residual load. Therefore, upward/downward flexibility demand in energy units is the surface area of the residual load curve on the positive/negative side of the curve.

To measure the flexibility in capacity units, we measure the change in the residual load over a certain period [232]. In this regard, upward/downward flexibility in capacity units refers to the need for flexible capacity due to an increase/decrease in the residual power load over a certain period.

In IESA-Opt-N, the flexibility demand can be satisfied by several flexible supply options: flexible generation, curtailment, demand response, storage, and cross-border electricity trade. The demand response refers to load shedding, load shifting, passive storage, and smart charging archetypes. The complete list of technological flexibility supply sources in the IESA-Opt-N model is presented in Table 47. This table indicates the name of the flexibility source, its primary sector, the name of the technology, and the number of different available technological options in the model.

Flexibility options and their underlying formulation in the IESA-Opt model (similar to IESA-Opt-N) are thoroughly explained [210]. Flexible generation includes power generation units, and CHPs, which provide flexibility in two dimensions: 1) by modifying their fuel input and 2) changing their heat-to-power ratio within a possible deviation range from a reference operation profile [136]. Demand response can be in the form of load shedding or load shifting. Load shedding requires the system to overinvest in the capacity [126] to allow a decrease in operation for hours when electricity is scarce and prices are high [125]. This flexibility form can be applied to various processes such as the production of heat [119], hydrogen [120], methanol [121], methane [122], hydrocarbons [152], chlorine [123], ammonia [124], and other chemicals [125]. In load shifting, the system reallocates the energy demand by increasing and decreasing it at different hours (always within a feasible operating range). For instance, power to X technologies are considered as load shifting technologies. Therefore, load shedding allows only for a one-direction variation in the demand, while load shifting allows for variations in demand in both directions.

As IESA-Op-N comprises all energy-related sectors of a country, it can endogenously determine the optimal mix of flexibility supply options. For instance, in the case of demand response (e.g., power to heat), the optimal amount of hourly heat demand is endogenously optimized based on the availability and hourly marginal price of electricity. This capability is one of the benefits of using a high-resolution ESM instead of a PSM. Although PSMs can provide higher technical resolution by including generation constraints and optimal power flow equations, they can hardly determine endogenous investment flexibility options in other sectors as they use exogenous sectoral demands. Therefore, the cross-sectoral flexibility investment usually remains an exogenous scenario parameter to PSMs.

Table 47. Cross-sectoral flexibility supply archetypes and corresponding technologies in the IESA-Opt model.

Flexibility source	Sector	example technologies
	Waste Disposal	CHP waste incineration
	Heat	CHP gas
Flexible Generation		CHP blast furnace gas
		CHP hydrogen
		CHP biomass
	Agriculture	CHP gas

	Power generation	Gas turbine, nuclear SMR plant
Demand Response	Industry	ULCOWIN steel production
		Solid state ammonia synthesis
	Refineries	P2Liquid Fischer–Tropsch
		P2Liquid methanol
	Hydrogen	Electrolyzer (Alkalyne, PEM, Solid Oxide)
	Residential	Electric heat pump with ground water
		Flexible standard electricity consumption
	Services	Flexible standard electricity consumption
Storage	Heat Network	Hot water storage tank
	Power generation	Compressed Air Energy Storage (CAES)
	Residential	Electric heat pump
	Transport	Electric battery vehicle smart charging
	Transport	V2G electric battery vehicle
Curtailment	Power generation	Wind, PV solar

6.2.4. **Theme two: uncertainty in technological costs**

One of the critical parameters to determine the optimal investment in technology is its costs. IESA-Opt-N segregates technological cost parameters into CAPEX, FOM, VOM, and fuel costs[47]. Moreover, four other parameters affect the cost calculations of a technology capacity investment: discount rate, construction time, decommissioning costs, and economic lifetime. Notably, the capital cost of new nuclear plants, construction times, and associated interest during construction (IDC) are significant factors in the decision-making for investments in new nuclear power plants in Western Europe [6]. Moreover, indirect service costs[48] are identified as crucial cost components of nuclear power, among other factors such as equipment costs, supplementary costs, material costs, and labor costs [233]. In this study, we are not interested in the share of each cost component. Therefore, we only use a single CAPEX component, which comprises the overnight construction costs, interest during construction, and other mentioned cost components. A recent study reported a wide range of 3.9 B€/GWe to 7.2 B€/GWe [221] for gen III nuclear capital costs. As there is vast uncertainty on nuclear capital cost estimates, we perform sensitivity analyses on this parameter.

Moreover, assumptions on social discount rates are crucial for the model-based assessment of renewables. Discount rates are used to determine the value of future cash

[47] For nuclear power, we consider the decommissioning and waste management costs as part of the VOM costs.

[48] Indirect services costs comprise field indirect costs, construction supervision, commissioning and startup costs, demonstration test run, design services off- and onsite, project/construction management services off- and onsite, and contingency on indirect services cost [307].

flows. The higher the discount rate, the lower the value we assign to future savings in today's decisions. The assumed discount rate differs widely across technologies and countries [234]. We assume a 5% discount rate for all technologies in the reference and nuclear scenarios. However, to identify the role of the discount rate in the economic feasibility of nuclear power, we perform a sensitivity analysis on this parameter.

We investigate the impact of technological cost variation on the cost-optimal investment decision in two separate sensitivity analyses. First, we fix VRES technological costs and analyze the change in nuclear investments by varying nuclear interest rates and CAPEX. Second, we fix the interest rate and analyze the impact of variations in VRES and nuclear CAPEX on investment decisions.

The nuclear scenario is used as the base for sensitivity analyses. Moreover, all sensitivity analyses are solved for the 2030, 2040, 2050, and 2060 periods to account for the energy transition dynamics.

Nuclear specific discount rate compared to nuclear capital cost

We analyze the sensitivity of the interest rate and capital costs on the investment in nuclear power plants. This analysis adopts optimistic VRES costs as described in Table 44. We assume four interest rate levels for investments in nuclear power generation depending on the source: 3% for public investments, 5% for public-private investments, 7% for low-risk private investments, and 9% for high-risk private investments. Furthermore, we vary the capital cost component of nuclear power generation from 3 B€/GW to 10 B€/GW with 0.5 B€/GW increments to account for variations in construction time and other cost variations.

VRES compared to nuclear capital cost

This sensitivity analysis demonstrates the impact of VRES and nuclear CAPEX changes on capacity investments. Here, we fix the interest rate for all technologies by assuming a public-private investment source with a 5% interest rate. We modify the capital cost component of nuclear power generation from 3 B€/GW to 10 B€/GW with 0.5 B€/GW increments. To account for changes in VRES costs, we change the CAPEX component of VRES across the minimum and maximum values we found in the literature. Table 48 demonstrates the utilized capital cost ranges for VRES technologies in 2050.

Table 48. The CAPEX cost range estimates for VRES technologies in 2050. Sources: [186], [78]

Technology	Lowest	Low	Mid	High	Highest
Wind offshore [M€/GW]	850	1250	1650	2050	2450
Wind onshore [M€/GW]	800	938	1075	1213	1350
Solar PV [M€/GW]	220	270	320	370	420

6.2.5. **Theme three: SMR and flexible generation**

Nuclear SMRs can change their output power by shutting down each small reactor, thus providing flexibility to the power system. However, the rate of power output change can differ for each design. Moreover, since SMRs are currently in low TRL levels, their cost estimates can vary significantly with the realization of projects. Therefore, to demonstrate the impact of nuclear generation flexibility (on several levels) on its economic feasibility, we frame a sensitivity analysis based on the nuclear scenario with changes in two parameters.

First, we modify the ramping rate of SMR technology in four subjective levels: 5%, 10%, 20%, and 60%. For instance, with the 5% ramping rate, the power output can increase or decrease only by 5% in each hour. This is rather a pessimistic assumption as standard load-following NPPs should ramp their output equal to 3% of nominal power per minute [235]. However, the aim here is to show the economic value of SMR flexibility in several ramping rate levels.

Second, we modify the capital cost of SMR in 2050 in the range of 5 B€/GW to 6.5 B€/GW with 0.1 B€/GW increments. The capital cost of gen III remains 6 B€/GW in 2050, as mentioned in the nuclear scenario definition. Therefore, we allow for investments in nuclear SMR while the total national installed capacity of gen III and SMR is capped at 12.48 GWe in 2050.

6.2.6. **Theme four: analyzing cross-border electricity trade**

Cross-border trade can play an essential role in supplying flexibility to the energy system [236]. However, the available cross-border electricity supply and demand and associated prices depend highly on the energy system states of the neighboring countries, which can vary drastically based on socio-political policies.

For instance, an in-depth review of model-based electricity generation scenarios of Germany and France is provided by Thimet et al. [237]. The power demand and generation mix in 2050 vary considerably across different scenarios for Germany. While some scenarios assume high shares of coal and natural gas in the power generation sector (e.g., [238], [239], and [240]), some others assume high shares of VRES (e.g., [241] and [238]). Moreover, the net imported electricity per year varies from 200 TWh [242] to more than -200 TWh [238] exports. Furthermore, the power demand varies from 500 TWh [239] to 1000 TWh [238] and even more than 1400 TWh [241].

Similarly, France's range of power demand and generation mix estimates in 2050 is moderately broad. In most scenarios, nuclear power and VRES remain the core of power generation in France (e.g., [243] and [244]). However, nuclear [9] or VRES [82] is the dominant power generator type in some scenarios. Moreover, the net imported electricity per year ranges from 50 TWh [245] to more than -200 TWh [195] exports in nuclear-based scenarios. While the French power demand ranges from slightly less than 300 TWh [246] to more than 700 TWh [244], most scenarios use demand values near 500 TWh.

This wide range of power demand and generation mix uncertainty across scenarios results in a wide range of estimated electricity prices and available cross-border trade capacity. Moreover, the range for Dutch electricity price estimates in 2050 is relatively wide: Koirala et al. [247] estimate the average Dutch electricity price of 148 €/MWh in 2050, which is highly sensitive to VRES capacity and electricity demand. Sijm et al. [248] report an average Dutch electricity price of 26 €/MWh assuming high investments in solar PV. However, IESA-Opt-N assumes lower solar potential, which results in higher electricity prices.

Power demand, generation mix, price, and trade capacity, can heavily affect the cost-effectiveness of national nuclear power investments. However, the estimations of these parameters for each neighboring country vary considerably. Thus, estimating the cross-border electricity price and volume projection can be demanding. In order to reflect this uncertainty on national nuclear investment decisions, we perform a set of sensitivity analyses. Taking the nuclear scenario as a base, we change the cross-border electricity price and its yearly volume to produce a set of sensitivity scenarios. Based on the available literature, we modify the electricity import price in the subjective range of 36 €/MWh to 155 €/MWh with 11 €/MWh increments. Since the model can decide when to export with the perfect foresight, we subjectively penalize the electricity export value by assuming the electricity export price equals 36 €/MWh lower than the import price at each step. Moreover, to account for the wide range of net imported electricity, we assume a moderately wide range of 0 to 111 TWh yearly electricity import (or export) volume. The model can invest in interconnection capacities if required; however, the total amount of imported or exported electricity remains under this maximum constraint.

6.3. Results and discussion

Following the same structure as the method section, the results are presented in four main themes: system-wide analyses, sensitivity analyses on technological costs, flexible generation, and cross-border trade. The reported values in this section are rounded to one or zero decimal digits to facilitate reading tables.

6.3.1. **Theme one: system-wide analyses**

Allowing for investment in nuclear power in the Netherlands has a significant impact on the energy system. Here we demonstrate this impact by comparing the reference and nuclear scenarios for major system indicators such as system costs, energy price, emission price, energy mix, flexibility volumes, and electricity trade.

Electricity mix

Under assumptions of the nuclear scenario, the model minimizes system costs by investing in 3, 5.9, and 9.6 GWe nuclear capacity in 2030, 2040, and 2050, respectively. Investments in nuclear power affect the power system in two ways: less VRES capacity and transmission line capacity requirements. In 2030, the 3 GWe nuclear capacity reduces offshore wind capacity by 4.7 GW and offshore transmission line capacity by 4.5 GW. In 2040, the wind offshore and its transmission line capacities will correspondingly reduce by 10.6 and 9 GW. Additionally, the import transmission line capacity reduces by 3.3 GW compared to the reference scenario. In 2050, the 9.6 GW baseload nuclear relieves the system from excessive investments in infrastructure, resulting in 5.7 and 10.9 GW less required capacity in offshore and cross-border transmission lines (Table 49).

Therefore, in early periods of the energy transition, nuclear power reduces the spatial challenges of VRES deployment by installing less offshore wind capacity. Moreover, in the long term, nuclear power contributes to a lower need for transmission line capacity, particularly cross-border and offshore capacities. However, the need for national transmission line capacity remains. Furthermore, the VRES capacities remain the same in 2050, as both scenarios hit the maximum VRES potential constraints.

Table 49. Evolution of electricity capacity mix in the reference and nuclear scenarios. Capacity values are rounded to one digit, and the units are in GW.

Scenarios	**Reference**			**Nuclear**			**Difference**		
Periods	2030	2040	2050	2030	2040	2050	2030	2040	2050
Offshore (far) Wind	13.3	36.1	65	8.6	25.5	65	-4.7	-10.6	0
Offshore (near) Wind	6	13	13	6	13	13	0	0	0
Onshore Wind	8	10	12	8	10	12	0	0	0
Solar (grouped)	40	63	75	40	63	75	0	0	0
Gas Turbines (grouped)	10.3	0	0	10.3	0	0	0	0	0
Nuclear	0.5	0	0	3.5	5.9	9.6	3	5.9	9.6
Other	4.6	0	0	4.6	0	0	0	0	0
Generation Capacity	82.7	122.2	165	81	117.5	174.6	-1.7	-4.7	9.6
Import interconnection capacity	10.8	26.6	39.2	10.8	23.3	32	0	-3.3	-7.2
Export interconnection capacity	10.8	10.8	24.3	10.8	10.8	20.6	0	0	-3.7
Offshore transmission capacity	14.1	33.8	71	9.6	24.8	65.3	-4.5	-9	-5.7
National transmission capacity	32	61.7	105.9	31	59	107.8	-1	-2.7	1.9
Total Capacity	150.4	255.1	405.4	143.2	235.4	400.3	-7.2	-19.7	-5.1

In the reference scenario, all electricity generation comes from VRES from 2040 onwards (Table 50). In the nuclear scenario, nuclear power contributes to 15% of electricity generation in 2040 and 2050, while offshore wind remains the primary cost-effective electricity generation source for the Netherlands.

Moreover, investments in nuclear power decrease the Dutch electricity dependence on neighboring countries resulting in 18.5 TWh less import in 2050. The imported and exported electricity amounts are low compared to the transmission line capacities, meaning that the model uses the cross-border electricity trade as a peak shaver with capacity factors between 0.16 (imports) and 0.31 (exports) in the nuclear scenario. Therefore, the cross-border electricity price plays an essential role in determining the hourly merit order curve and the need for investments in nuclear power. The sensitivity analyses in section 6.3.4 explore further the role of cross-border trade.

Table 50. Evolution of electricity generation mix in the reference and nuclear scenarios. Units are in TWh. Values are rounded to one digit.

Scenarios	**Reference**			**Nuclear**			**Difference**		
Periods	2030	2040	2050	2030	2040	2050	2030	2040	2050
Offshore (far) Wind	64.6	166.8	321.8	42.2	118.8	312.8	-22.4	-48	-9
Offshore (near) Wind	31.7	68.6	68.6	31.7	68.6	68.6	0	0	0
Onshore Wind	20	21.3	28.4	20.2	22.1	28.3	0.2	0.8	-0.1
Solar (grouped)	31.2	49	58.3	31.2	49	58.3	0	0	0
Gas Turbine (grouped)	1.8	0	0	1	0	0	-0.8	0	0
Nuclear	3.8	0	0	27.5	46.5	75.8	23.7	46.5	75.8
National Generation	153.2	305.8	477.1	153.9	305.1	543.8	0.7	-0.7	66.7
Imported Electricity	27.8	33.3	34	27.8	33.3	15.5	0	0	-18.5
Exported Electricity	3.6	22.3	44.4	3	21.4	44.4	-0.6	-0.9	0
Total Electricity Demand	177.4	316.8	466.7	178.7	317	514.9	1.3	0.2	48.2

Although the electricity demand does not differ between the scenarios in 2030 and 2040, it increases considerably in the nuclear scenario in 2050. This increase is mainly due to higher electricity demand in producing hydrogen, by Solid Oxide Electrolyzer, and ammonia, by Solid State Ammonia Synthesis. The produced hydrogen is used in hydrogen boilers, resulting in a lower need for natural gas. In addition, the Solid-State Ammonia Synthesis production replaces the Haber Bosch Steam Methane Reforming technology, consequently reducing natural gas demand. Due to lower natural gas demand, the need for syngas production from biomass gasification reduces. Therefore, investments in nuclear power result in lower electricity, natural gas, and biomass imports (Figure 54).

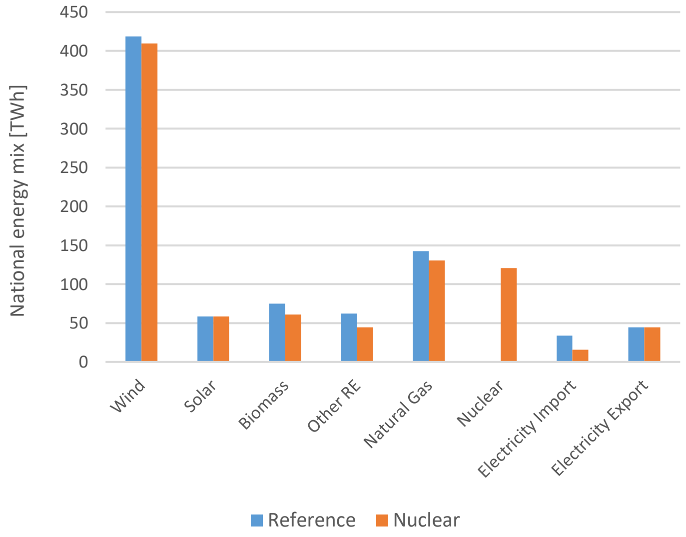

Figure 54. The 2050 primary energy mix in the reference and nuclear scenarios in the Netherlands.

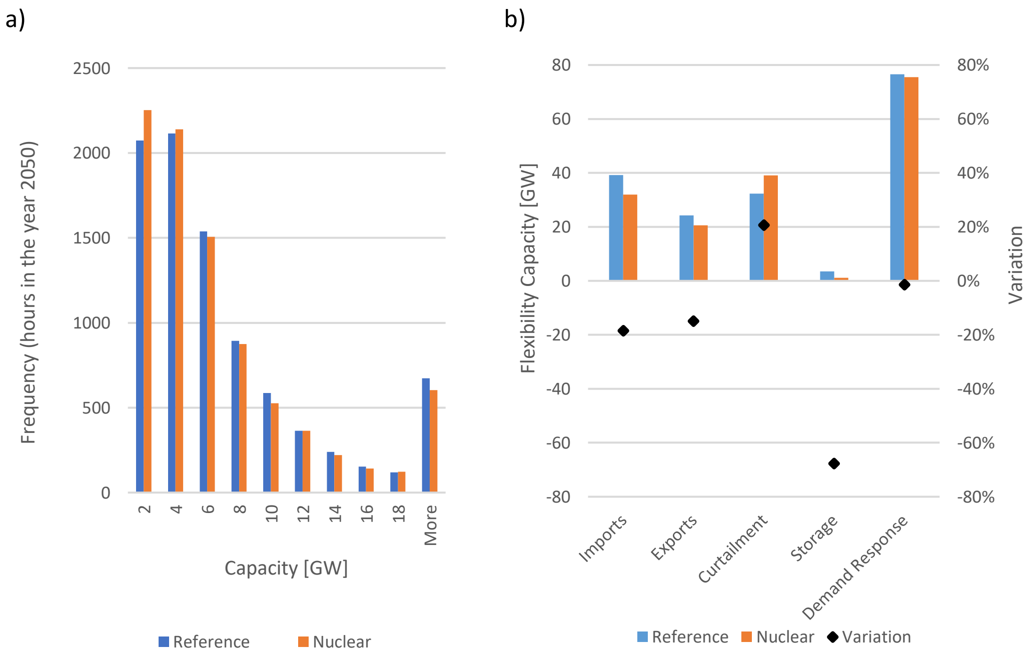

Figure 55. Flexibility supply by capacity.
a) the cumulative histogram of the flexibility capacity demand in the reference and nuclear scenarios in 2050.
b) variations in flexibility supply capacity by source in the nuclear scenario compared to the reference scenario in 2050.

Flexibility supply in units of capacity (GW)

Figure 55-a demonstrates the histogram of the required flexibility capacity to balance the hourly variations in the residual load in 2050. Both scenarios require high levels of flexible capacity. However, there are more hours with low flexibility capacity in the nuclear scenario and fewer hours with high flexibility capacity. Therefore, the flexibility demand shifts from higher to lower capacities in the nuclear scenario.

Although Figure 55-a demonstrates the trend in lower demand for flexibility in the nuclear scenario, it does not provide details regarding the flexibility supply sources. The flexibility demand is satisfied by several flexibility supply sources that are presented in Figure 55-b. The values in this figure refer to the maximum capacity supplied by each source during each hour of 2050. In the nuclear scenario, the capacity required to satisfy the flexibility demand reduces by all sources, except curtailment, which increases mainly due to lower investments in the offshore wind transmission line. Moreover, the required storage capacity is reduced by 68% in the nuclear scenario. Therefore, investments in nuclear can highly influence the demand for electricity storage and cross-border transmission line capacity. The reduction in the required demand response capacity is negligible, suggesting that the energy system also relies heavily on demand response by 2050 with low carbon baseload power generation.

Flexibility supply in units of energy (TWh)

Figure 56 demonstrates the hourly residual load curve and flexibility supply sources of the reference scenario in 2050. In order to balance the residual load, the energy system can use several flexibility supply options such as flexible generation, storage, demand response, curtailment, and cross-border trade (i.e., electricity imports and exports). The positive residual load can be balanced by flexible generation, storage, demand response, or electricity import and the negative residual load by demand response, storage, curtailment, and electricity exports.

Since VRES dominates the reference scenario, the residual load is negative in most hours. However, this negative residual load is mainly balanced by high demand response and curtailment values. The demand response here mainly refers to the production of hydrogen (i.e., electrolyzers), ammonia (i.e., solid-state synthesis), and methanol (P2Liquids).

By adding all hourly volumes of flexibility supply in Figure 56, we can compare yearly flexibility supply volumes in the reference and nuclear scenario in Figure 57. The demand for flexibility volume increases by 54.4 TWh (equal to 30%) in the nuclear scenario in 2050. This considerable increase is mainly due to overinvestments in producing syngas from Solid-Oxide electrolyzer technology resulting in higher load shedding volumes. Due to lower electricity prices, the extra investments in these technologies become cost-effective in the nuclear scenario. Additionally, the curtailment volume increases by 35%, meaning that the model prefers to avoid the high costs of the offshore transmission line as the average electricity price in 2050 is reduced by 16% in the nuclear scenario. However, since VRES curtailment depends on exogenous wind and solar profiles, we might observe an utterly different curtailment behavior by the system with a slightly different set of profiles. Moreover, the need for electricity storage options reduces by 6.7 TWh in the nuclear scenario due to lower Compressed Air Underground Storage utilization.

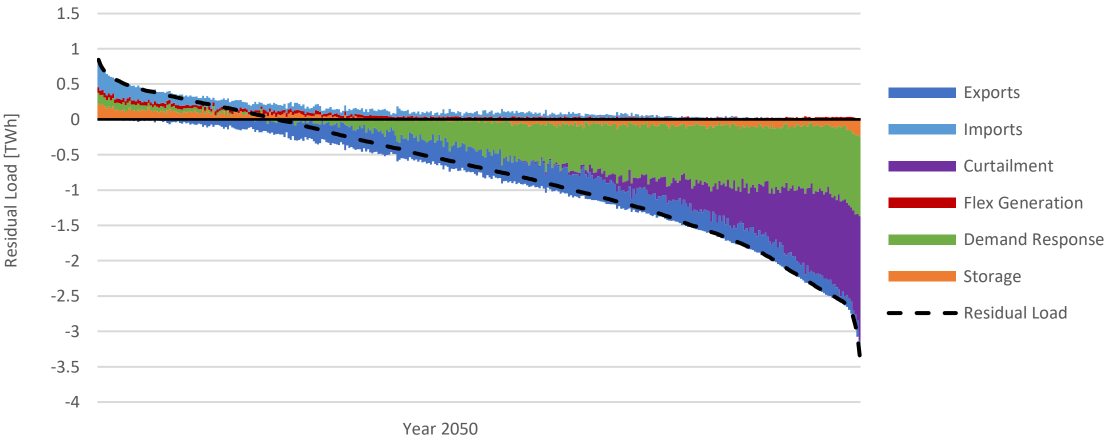

Figure 56. The reference scenario's residual load curve and flexibility supply sources in 2050. The substantial negative residual load is mostly balanced through demand response and curtailment.

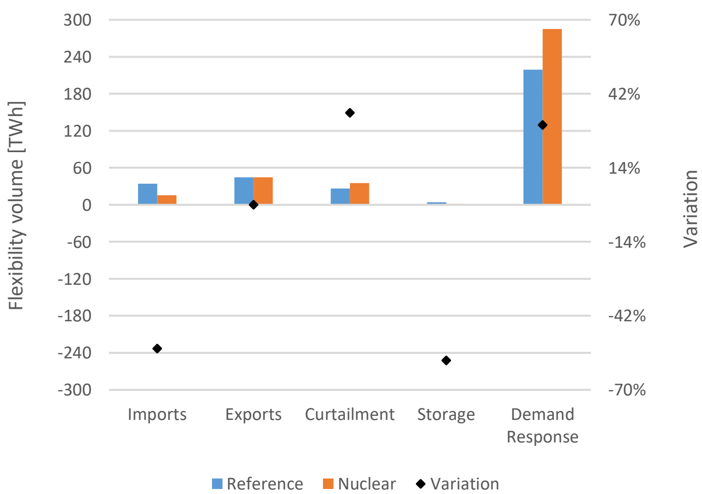

Figure 57. Variations in the flexibility volume by source in the nuclear scenario compared to the reference scenario in 2050.

Although the electricity export volume remains the same, the electricity import volume decreases by 54% in the nuclear scenario. The reduction in electricity import both in capacity and volume suggests that investments in nuclear power directly reduce the Netherlands' long-term dependency on electricity trade.

System costs

Investments in nuclear power reduce the national system costs by 0.19 B€ (equal to 0.2%) and 1.24 B€ (equal to 1.1%) in 2040 and 2050, respectively (Table 51). This outcome may sound counterintuitive considering the higher costs of nuclear power than other electricity generation sources. However, nuclear investments affect the whole energy system. Although the capital and fixed operational costs increase (mainly due to higher nuclear investments), the variable operational and trading costs reduce substantially (mainly due to lower electricity import costs), resulting in lower overall system costs in 2050. In conclusion, given all the cost uncertainties, the system cost reduction is not significant.

Table 51. National system cost (in $B€_{2019}$) evolution in the reference and nuclear scenarios. System costs are 0.2% and 1.1% lower in the nuclear scenario in 2040 and 2050.

Scenarios	**Reference**			**Nuclear**			**Difference**		
Periods	2030	2040	2050	2030	2040	2050	2030	2040	2050
Capital Cost	51.9	61.1	63.3	51.6	60.4	64.6	-0.32	-0.64	1.24
Fixed Operational Cost	30.0	32.6	38.5	30.2	32.7	39.5	0.16	0.03	1.01
Variable Operational Cost	96.8	79.6	10.0	96.9	80.1	8.7	0.08	0.49	-1.37
Trading Cost	-67.2	-48.3	0.4	-66.9	-48.4	-1.7	0.31	-0.07	-2.13
Total System Cost [B€]	111.6	125.0	112.2	111.8	124.8	111.0	0.24	-0.19	-1.24

In the short term (i.e., 2030), although capital costs decrease in the nuclear scenario (due to lower investments in offshore wind), the system costs increase slightly. This is due to a higher fixed operational cost of nuclear power and higher trading costs (i.e., lower export revenues). On the other hand, the lower export revenue results from the export product cost reduction, mainly due to cheaper electricity prices in the nuclear scenario.

Mitigation costs

Comparing the mitigation costs provides a better indication of system-wide cost implications of a specific energy policy. Compared to the reference scenario, the sum of mitigation costs in the transition pathway is lower in the nuclear scenario (Figure 58-a). In 2030, the mitigation costs will increase slightly by 2.8% (equal to 0.2 B€) in the nuclear scenario. However, in the long term, nuclear investments reduce the mitigation costs by 1.6% (0.3 B€) and 6.2% (1.3 B€) in 2040 and 2050, respectively.

These cost values refer to annualized costs occurring in a specific year. In order to estimate the cumulative mitigation costs, we can linearly interpolate the cost values for the years in-between (Figure 58-b). Consequently, the estimated cumulative mitigation costs from 2030 to 2050 are equal to 361.2 B€ and 352.2 B€ in the reference and nuclear scenarios, respectively. Therefore, investments in nuclear power can reduce the cumulative mitigation costs by 2.5% (9 B€) up to 2050.

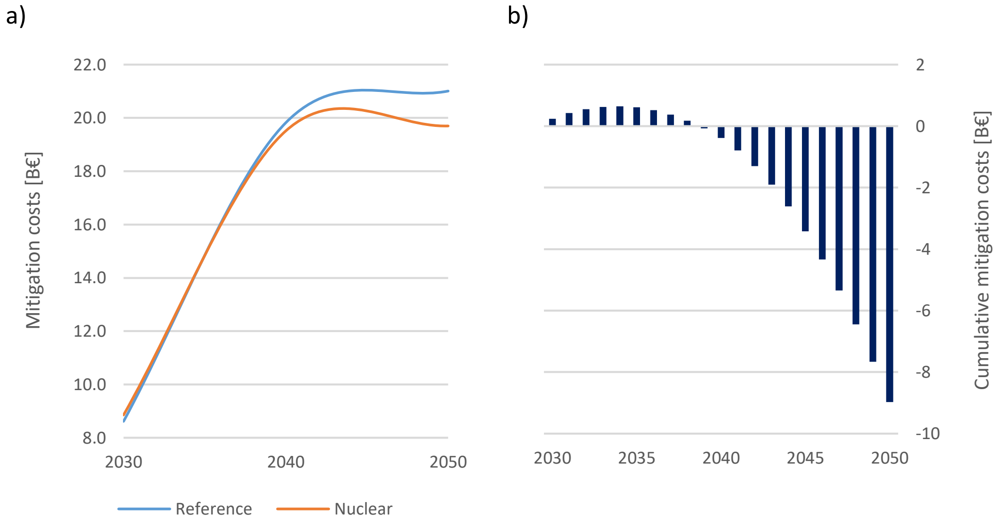

Figure 58. Mitigation costs. a) Mitigation costs (B€$_{2019}$) evolution in the reference and nuclear scenarios. Nuclear scenario mitigation costs increase slightly in 2030 but reduce in the long term. b) The interpolated cumulative mitigation costs in the nuclear scenario minus the reference scenario. Investments in nuclear power reduce cumulative mitigation costs by 9 B€ in the long term.

Final sectoral costs

In the nuclear scenario, most final sectors experience cost reduction in 2050 (Figure 59-a). Residential and services sectors experience 10% cost reduction, mainly due to lower electricity prices. Similarly, the cost reduction in the industrial (12%) and transport (4%) sectors results mainly from lower fuel costs as the endogenous price of electricity, bio ethanol, hydrogen, syngas, and bio kerosene fuels decreases.

The average final energy cost in both scenarios reduces in the long term. This is mainly due to the higher share of VRES in power generation and, thus, lower electricity prices. Compared to the reference scenario, the final energy cost in the nuclear scenario decreases by 1%, 3%, and 9% in 2030, 2040, and 2050, respectively (Figure 59-b). This reduction is mainly due to the higher electrification rate and cheaper electricity prices in the nuclear scenario, particularly in 2050. Thus, on average, investments in nuclear power reduce the final consumer's energy costs.

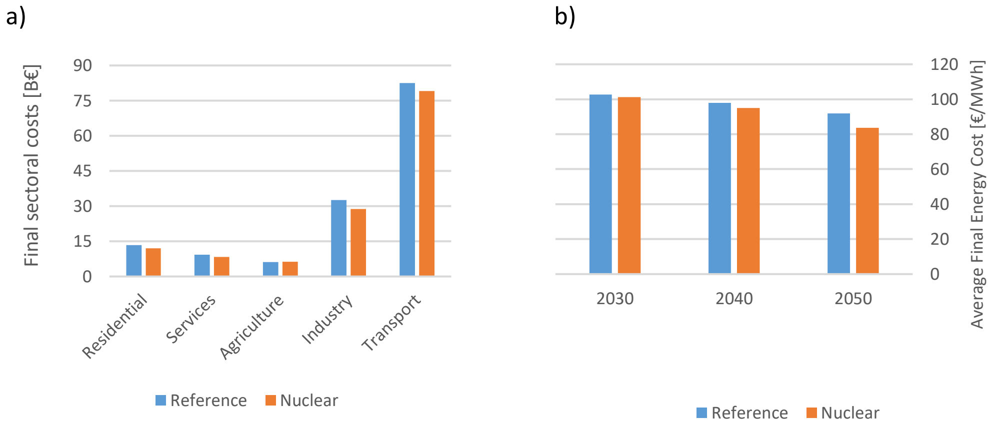

Figure 59. Final sectoral costs. a) Final system costs by sector in the reference and nuclear scenarios in 2050 (in B€$_{2019}$). b) Average final energy cost evolution in the reference and nuclear scenarios.

Power generation sector costs

Power generation costs increase by 2%, 4%, and 9% in 2030, 2040, and 2050, respectively (Table 52). The cost increase in 2030 and 2040 is mainly due to the higher FOM and VOM of nuclear power. In 2050, the cost will increase considerably, mainly due to higher electricity demand and extra investments in nuclear power. However, import costs are reduced by more than half compared to the reference scenario.

Table 52. Decomposition of power generation sector costs in the reference and nuclear scenarios, 2030-2050 (in B€$_{2019}$).

Scenarios		**Reference**			**Nuclear**			**Difference**		
Periods		2030	2040	2050	2030	2040	2050	2030	2040	2050
Balancing	CAPEX [B€]	10.1	15.2	21.9	9.8	14.8	24	-0.3	-0.4	2.1
	FOM [B€]	2.1	4	6.4	2.3	4.1	7.5	0.2	0.1	1.1
	VOM [B€]	0.2	0.2	0.3	0.5	1	1.6	0.3	0.8	1.3
	Fuel Costs [B€]	0.1	0	0	0.2	0.2	0.4	0.1	0.2	0.4
	Import Costs [B€]	1.6	2.9	3.9	1.6	2.9	1.8	0	0	-2.1
	Export Revenues [B€]	-0.1	-1.1	-3.5	-0.1	-1.1	-3.5	0	0	0
Total Costs [B€]		14.1	21.2	29.1	14.3	21.9	31.7	0	1	3
Capacity (generation + transmission) [GW]		150.4	255.1	405.4	143.2	235.4	400.3	-7	-20	-5
Demand [TWh]		178.1	347.1	408	182.9	465.8	553.3	4.8	118.7	145.3
Average Electricity Price [€/MWh]		119.8	89	91.9	111.8	85.2	77.2	-8	-4	-15

The endogenous power demand in 2050 increases considerably in the nuclear scenario. Thus, we compare power sector costs per total electricity demand. We see a 1% and 3% cost increase in the nuclear scenario in 2030 and 2040, respectively, compared to the reference scenario. However, in 2050, the power sector costs per unit of electricity demand will be reduced by 1% with investments in nuclear. Therefore, although the total power sector costs increase in the nuclear scenario, the cost per unit of demand decreases, which results in a 16% lower average electricity price in 2050.

The average electricity price refers to the average hourly shadow price of the electricity balancing constraint. Investments in nuclear power decrease the average electricity price by 7%, 4%, and 16% in 2030, 2040, and 2050, respectively. Investments in relatively expensive nuclear power decrease electricity prices because it reduces the need for flexibility supply options. The price duration curve in Figure 60 demonstrates that the nuclear scenario has lower electricity prices than the reference scenario in most hours of the year.

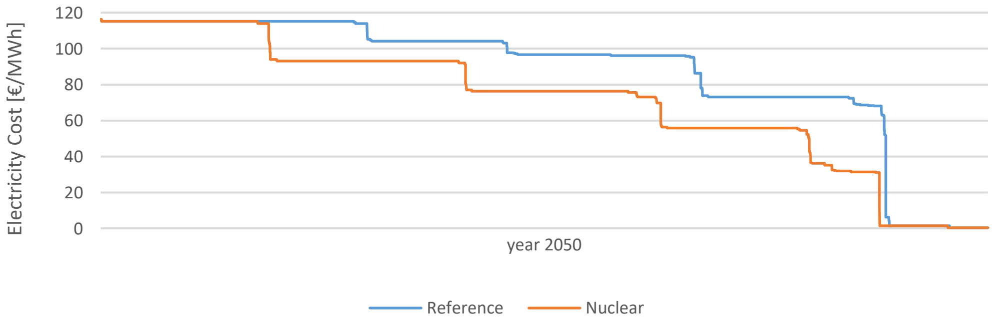

Figure 60. The electricity price duration curve of the Netherlands in the reference and nuclear scenarios in 2050.

Emissions

The model optimally distributes the emissions between ETS and non-ETS sectors to achieve the 55%, 77%, and 100% emission reduction targets in 2030, 2040, and 2050, respectively. Investing in nuclear power allows for 5.6 Mton (20%) more non-ETS emissions in 2050, as the ETS sector can utilize the cheaper electricity to capture emissions further. The higher negative ETS emission mainly comes from the lower emitted CO_2 from the Haber Bosch ammonia production with Steam Methane Reforming. Due to higher negative emissions, the non-ETS sector increases its emissions, which are emitted from gas boilers in the residential sector.

We report the national CO_2 shadow price as an output of the model for the national emission constraint that covers both ETS and non-ETS emissions. The emission price in both scenarios decreases in the long term. Although the CO_2 price does not change noticeably in 2030 and 2040, it is reduced by 25% in the nuclear scenario in 2050. The lower emission price is directly related to cheaper electricity prices, resulting in higher electrification of the industry.

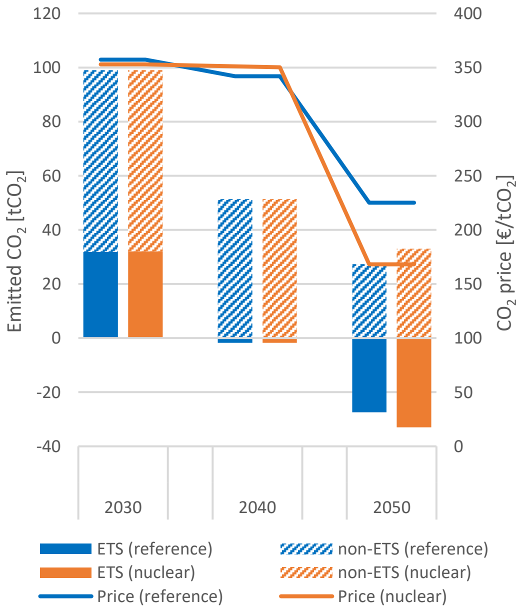

Figure 61. The evolution of ETS and non-ETS emissions and total CO_2 shadow price in the reference and nuclear scenarios.

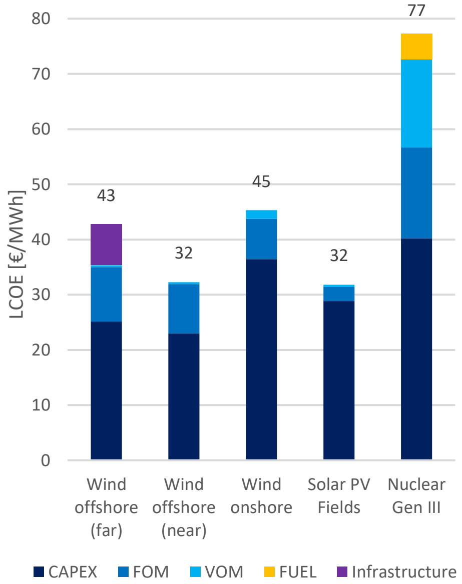

Figure 62. The realized LCOEs under the nuclear scenario in 2050 for intermittent renewables and nuclear technologies.

LCOEs

Resulting from the nuclear scenario, Figure 62 presents the realized LCOE of VRES and nuclear power generation technologies in 2050. Wind offshore LCOE includes an infrastructure component that refers to required extra investments in submarine cables to connect far offshore wind farms to the national grid. However, the national grid infrastructure cost component is not included as all generation technologies share this infrastructure. Although nuclear power has a considerably higher LCOE than wind offshore, the system invests in it to avoid relatively higher indirect system-wide costs such as higher flexibility supply costs and higher infrastructure capacity demand. For instance, since nuclear power partly substitutes wind offshore, the indirect system-wide cost component of LCOE for wind offshore is at least equal to the difference between the wind and nuclear LCOEs, which is 34 €/MWh. However, the indirect system-wide cost component of LCOE is highly dependent on the system configuration, scenario assumptions, and exogenous VRES profiles. Therefore, assuming a specific value as the indirect system cost across different scenarios can be misleading. Instead, we suggest applying a whole energy system-wide modeling approach, as it is done in this study, to account for system-wide costs in energy system planning analyses. In conclusion, relying merely on LCOE analyses can underestimate the role of nuclear power in the energy system. This is in line with the conclusion from Hansen [249] that looking beyond LCOE values significantly changes the energy system's priorities.

6.3.2. **Theme two: Uncertain technological costs**

We run the nuclear scenario for the sensitivities in 2030, 2040, 2050, and 2060 periods. However, only the 2050 values are reported here. Furthermore, we decreased the model's temporal resolution to save computational time.

6.3.2.1 Interest rate compared to nuclear capital costs

The financial source of the investment can significantly impact the economic feasibility of nuclear power. Figure 63 demonstrates that in higher discount rates, the investments in nuclear power become more sensitive to nuclear capital cost variations. Moreover, assuming a public investment, nuclear power is a cost-effective technology option in 2030 and 2050.

In 2050, with public investments in nuclear (i.e., 3% discount rate), capital costs up to 10 B€/GW are still economical. With public-private investments (i.e., a 5% discount rate), the maximum economical nuclear capital cost is around 9 M€/GW. In contrast, low-risk private investments in nuclear (i.e., 7% discount rate) reduce the maximum economic nuclear capital cost to 6.5 B€/GW. However, with high private investment risks (i.e., a 9% discount rate), only capital costs less than 5 B€/GW can be cost-effective. In 2030, nuclear investments become more sensitive to nuclear capital cost variations in higher discount rates. While the system invests the maximum allowed nuclear capacity with the public discount rate, the maximum economic nuclear capital cost reduces to 8.5, 6, and 4.5 B€/GW with discount rates of 5%, 7%, and 9%, respectively. Therefore, assuming public interest rates for financing nuclear power investments can significantly reduce the relevance of nuclear capital cost uncertainties both in the short and long term.

This outcome is highly relevant to the EU sustainable finance taxonomy. The EU taxonomy would provide companies, investors, and policymakers with appropriate definitions for which economic activities can be considered environmentally sustainable. In this way, it creates security for investors in environmentally sustainable activities [250]. Since nuclear power can drastically reduce mitigation costs, the European Commission has investigated including nuclear power in the EU taxonomy list [251]. Although nuclear power is not listed in the primary definition of EU taxonomy, the European Commission approved a Complementary Climate Delegated Act, in which nuclear power is added to the list under certain conditions [252]. As a result, the wide range of nuclear CAPEX estimates has a limited impact on nuclear power investments as it benefits from EU taxonomy.

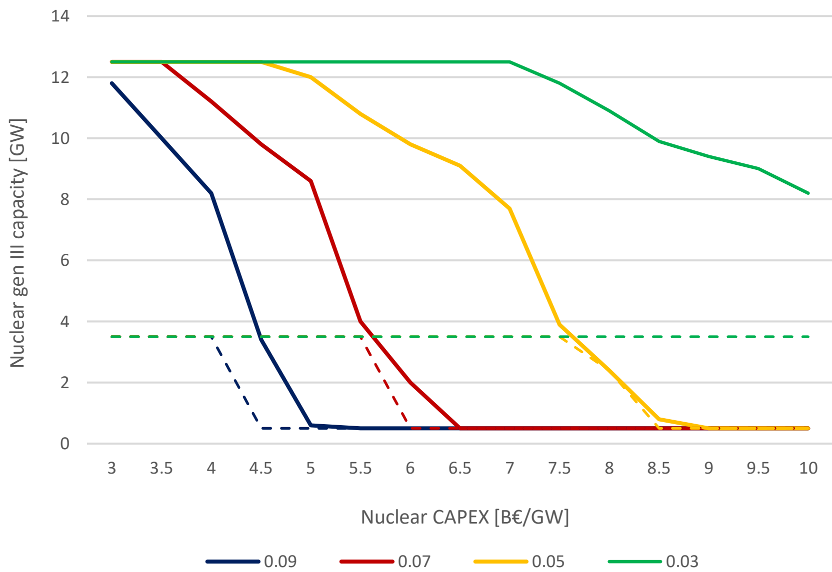

Figure 63. The installed nuclear gen III capacity variations with different nuclear interest rates and capital costs.

Straight lines refer to 2050 investments, while dashed lines indicate the investments in 2030.

6.3.2.2 VRES compared to nuclear capital costs

As shown in Table 53, by assuming an equal discount rate of 5% for all technologies, nuclear with 9.5 B€/GW CAPEX and above is not competitive unless VRES costs reach the highest estimates. However, even with optimistic VRES CAPEX estimates, investments in nuclear power can be cost-effective with nuclear CAPEX under 8 B€/GW. Although with higher VRES CAPEX values, the nuclear investments' range shifts to more expensive nuclear CAPEX values, the range of this sensitivity remains almost the same. Therefore, variations in VRES CAPEX estimates do not change nuclear investments' sensitivity on nuclear CAPEX values.

Table 53. Installed nuclear generation capacity with variations in the VRES capital costs against nuclear capital costs. The numerical values of VRES CAPEX are described in Section 0.

VRES CAPEX	Nuclear gen III capacity [GWe] in 2050											
Highest	12.5	12.5	12.5	12.5	12.5	9.5	7.6	3.7	3.5	3.5	1.2	0.5
High	12.5	12.5	12.5	9.5	9.4	8.2	4.5	3.5	3.5	1.3	0.5	0.5
Mid	12.5	12	10.9	9.6	8.9	7.7	3.9	3.5	1.2	0.5	0.5	0.5
Low	12.5	12	10.9	9.8	8.8	7.7	4	2.1	0.5	0.5	0.5	0.5
Lowest	12.5	12	10.9	9.8	8.7	8	4	1.9	0.5	0.5	0.5	0.5
	4.5	5	5.5	6	6.5	7	7.5	8	8.5	9	9.5	10
	Nuclear CAPEX [B€/GW]											

VRES capacity in Table 54 refers to the sum of wind offshore, wind onshore, and solar PV capacities in 2050. In the low and lowest VRES CAPEX estimates, the VRES capacity investments hit the maximum exogenous potential, irrespective of nuclear CAPEX value. With higher VRES CAPEX estimates, the VRES investments reduce by lower nuclear CAPEX values. However, this variation is not significantly sensitive to nuclear CAPEX values. Moreover, with the highest estimates of VRES CAPEX, the installed capacity reduces by 3% compared to the lowest cost estimates. Therefore, VRES investments are cost-optimal for the energy system irrespective of VRES and nuclear CAPEX estimate levels under the nuclear scenario assumptions.

Table 54. VRES generation capacity with variations in the VRES capital costs against nuclear capital costs. The numerical values of VRES CAPEX are described in Section 0.

VRES CAPEX	VRES generation capacity [GWe] in 2050									
Highest	158.7	158.7	158.7	158.7	158.7	158.7	158.7	158.7	162.7	165
High	161.3	161.3	161.3	161.3	161.3	161.3	165	165	165	165
Mid	164.7	164.7	164.7	164.7	165	165	165	165	165	165
Low	165	165	165	165	165	165	165	165	165	165
Lowest	165	165	165	165	165	165	165	165	165	165
	3	3.5	4	4.5	5	5.5	6	6.5	7	7.5
	Nuclear CAPEX [B€/GW]									

6.3.3. **Theme three: Flexible generation**

The cost-optimal national SMR investment can vary considerably with its ramping rate and CAPEX estimates. The assumed nuclear gen III CAPEX value in 2050 is 6 B€/GW.

Table 55 shows that at the 6 B€/GW SMR CAPEX value, the investments in SMR increase slightly with higher ramping rates. With 0.2 B€/GW more SMR CAPEX value (i.e., 6.2 B€/GW), the model only adopts this technology if its ramping rate is higher than 60%. Therefore, the provided generation flexibility of SMR can only make up for 0.2 B€/GW higher CAPEX costs compared to gen III. Moreover, SMR investments are highly susceptible to variations in the SMR CAPEX value, irrespective of their ramping rate. Therefore, any cost reduction in SMR compared to gen III leads to considerably higher investments in SMR. Additionally, although the investments in SMR capacity increase with higher ramping rates (i.e., generation flexibility), this increase does not change considerably in different CAPEX values. Thus, compared to SMR ramping rate (i.e., providing generation flexibility), the SMR CAPEX value is the dominant parameter in determining its investments.

In conclusion, the investment choice between SMR or gen III depends highly on their CAPEX rather than the flexibility of SMR. The value of SMR flexibility supply becomes noticeable only in a narrow range of SMR CAPEX. Therefore, decreasing SMR CAPEX can considerably impact its economic feasibility compared to increasing its flexible generation potential.

Table 55. Investments in SMR nuclear with variations in its ramping rate and CAPEX in 2050.

Ramping Rate	Nuclear SMR capacity [GWe] in 2050							
60 %	9	9	8.6	8	7.4	6.8	6.4	0
20 %	9	8.8	8.2	7.5	7	6.5	0	0
10 %	9	8.4	7.9	7.2	6.8	6.3	0	0
5 %	8.9	8.3	7.8	7.1	6.7	6.2	0	0
	5	5.2	5.4	5.6	5.8	6	6.2	6.4
	SMR CAPEX [B€/GW]							

6.3.4. **Theme four: Cross-border electricity trade**

This section aims to quantify the sensitivity of national nuclear power investments to cross-border electricity trade potential, notably its price and volume. Therefore, the presented numbers in the tables should not be used as a conclusion per se, but the overall behavior of the energy system as a response to variations in cross-border trade parameters.

Table 56. Investments in nuclear gen III capacity with variation in electricity price and trade quota in 2050. Area A (i.e., cells with a red border) and B (i.e., cells with a blue border) are further examined in the following sensitivity analyses.

Electricity Price [€/MWh]	Nuclear gen III capacity [GWe] in 2050								
155	10.4	9.5	10.9	12.3	12.5	12.5	12.5	12.5	12.5
144	10.4	9.5	10.4	11.5	12.5	12.5	12.5	12.5	12.5
133	10.4	9.5	9.7	10.8	12.3	12.5	12.5	12.5	12.5
122	10.4	9.5	9.2	9.9	11.2	12.5	12.5	12.5	12.5
112	10.4	9.5	8.4	8.8	10.3	12	12.5	12.5	12.5
101	10.4	9.5	7.3	7.8	9.5	9.7	9.7	9.7	9.8
90	10.4	9.5	5.1	4	3.5	3.5	3.5	2.6	1.1
79	10.4	9.5	4.7	3.5	3.5	3.5	2.6	0.5	0.5
68	9.9	9.5	4.6	3.5	3.5	3.5	2.2	0.5	0.5
58	9.9	9.4	4.4	3.5	3.5	3.4	1.9	0.5	0.5
47	9.9	9.1	4.3	3.5	3.5	2.4	1	0.5	0.5
36	9.9	9.1	4.3	3.5	3.5	2.3	0.8	0.5	0.5
	0	14	28	42	56	69	83	97	111
	Electricity trade (import or export) quota in 2050 [TWh]								

The electricity price and trade volume quota can considerably affect the investments in nuclear power (Table 56). The electricity quota indicates the maximum yearly traded electricity in imports or exports. In low trade quotas (i.e., no trade or a maximum of 14 TWh), the investments in nuclear do not change with electricity price variations. With higher trade quotas, nuclear power becomes more cost-effective or less, depending on electricity prices. With lower electricity prices (i.e., under 90 €/MWh), nuclear investments reduce with the higher trade quota, as the imported electricity can substitute nuclear power demand. With higher electricity prices, the model increases the investments in nuclear power as the higher exported electricity revenue justifies nuclear power costs. Consequently, investments in nuclear are not noticeably sensitive to electricity trade volumes by assuming imported electricity prices higher than 112 €/MWh in 2050.

From 14 TWh to 28 TWh quota, the investments in nuclear drop considerably at lower prices. Therefore, a red cell border in Table 56 determines this sensitive area (i.e., area A). Moreover, investments in nuclear increase significantly from 90 to 112 €/MWh import prices. Therefore, this sensitive area (i.e., area B) is indicated with a blue cell border. In the following, we zoom into these sensitive areas.

Area A

In low electricity prices, the cost-effective investments in nuclear power depend considerably on trade quotas (Table 57). By increasing the trade quota by 14 TWh, the need for nuclear capacity can reduce by half. However, in higher electricity prices, this reduction is considerably lower (i.e., only 1 GW reduction). Therefore, cost-effective nuclear investments can be susceptible to trade volumes in low electricity price forecasts.

Table 57. The zoom-in area A of Table 56

Electricity Price [€/MWh]	Nuclear gen III capacity [GWe] in 2050					
112	9.5	9	8.6	8.2	8.2	8.4
101	9.5	8.7	8.3	7.8	7.3	7.3
90	9.5	8.3	7.9	7.1	6.3	5.1
79	9.5	8.3	7.4	6.5	5.8	4.7
	14	17	19	22	25	28
	Electricity trade quota in 2050 [TWh]					

Area B

With a high electricity trade volume, nuclear power investments increase considerably with electricity prices higher than 94 €/MWh (Table 58). With these prices, nuclear capacity can contribute to higher revenues from exports; thus, nuclear investments increase with higher trade quotas. Therefore, with high electricity trade volumes, the cost-optimal nuclear power investments are susceptible to electricity price variations in 90 to 112 €/MWh.

Table 58. The zoom-in area B of Table 56

Electricity Price [€/MWh]	Nuclear gen III capacity [GWe] in 2050								
112	10.4	9.5	8.4	8.8	10.3	12	12.5	12.5	12.5
108	10.4	9.5	8	8.3	9.9	11.9	12.5	12.5	12.5
104	10.4	9.5	7.7	8	9.8	11.7	12.5	12.5	12.5
101	10.4	9.5	7.3	7.8	9.5	9.7	9.7	9.7	9.8
97	10.4	9.5	6.7	7.6	6.2	6.5	6.6	7	7.1
94	10.4	9.5	5.7	4.9	3.5	3.5	3.5	3.5	2
90	10.4	9.5	5.1	4	3.5	3.5	3.5	2.6	1.1
	0	14	28	42	56	69	83	97	111

Electricity import and export quota in 2050 [TWh]

6.4. Discussion

There are not many studies focusing on the role of nuclear power in the national energy transition, using a highly detailed energy system optimization model, so opportunities to compare our results with other works have been limited. While some reviewed studies suggest the economic feasibility of nuclear power, some others disagree. Furthermore, we have shown that cost-effective nuclear investments depend on several techno-economic parameters. Thus, conclusions on the economic feasibility of nuclear power in an energy system with high shares of VRES should be accompanied either by robust reasoning regarding cost and cross-border trade assumptions or sensitivity analyses.

Uncertain weather

In this study, we performed several sensitivity analyses to showcase the role of some sensitive parameters. However, in all of these scenarios, the assumed weather year was similar resulting in similar wind and solar availability profiles. In such a “normal” profile, there are no long periods of low wind and solar availability, known as “dunkelflaute”.

In order to provide robust results, the model should include weather uncertainties either by updated formulation or sensitivity analyses. The cost-effective transition pathway can vary drastically depending on availability of wind and solar energy and flexibility demand of the energy system.

Assumed discount rates

To avoid any bias for VRES or nuclear, we assumed the same 5% discount rate for all technologies in the reference and nuclear scenarios. However, the sensitivity results showed that the value of the discount rate considerably affects the cost-effectiveness of nuclear investments. Therefore, for future studies, we suggest using technological-specific discount rates based on national or international policies (e.g., EU taxonomy).

Social Discount rate

In the empirical literature, there exist many studies that support a social discount rate that is declining over time ([253], [254], [255]). This is relevant for studies that base their conclusions on the social discount rate value (e.g., discounted cash flow analyses). However, we use the social discount rate to weigh different periods in the objective function. For example, the weight of each period in the objective function is 1/3 if we assume a zero social discount rate; while assuming a 2% social discount rate, the weights are 0.4, 0.33, 0.27 for the 2030, 2040, and 2050 periods, respectively. In this formulation, changing the social discount rate (through using a declining social discount rate) does not affect the conclusions considerably.

Cross-border electricity trade

The sensitivity analyses on cross-border trade indicate that the electricity trade price and quota considerably affect the investments in nuclear power. Additionally, the evolution of the European electricity market, particularly the Netherlands' neighboring countries, is highly uncertain. Therefore, following a coordinated electricity trade policy with neighboring countries significantly reduces the uncertainty of nuclear power investments.

Nuclear cogeneration

This study analyzed the nuclear energy source as a power generation technology only. However, fission heat can also be used directly for district heating or as a process-heat in the industry, thus replacing carbon-intensive heat sources like natural gas. Additionally, nuclear plants can be operated in cogeneration mode and deliver a share of fission heat as a final heat source while generating electricity. The resulting higher efficiency may result in more profitable power plants.

Worldwide already sixty-seven nuclear reactors are being operated in cogeneration mode, satisfying district heating, desalination, and industrial process heat demands [256]. Nuclear cogeneration can satisfy process heat demand requiring steam at temperatures up to 550 °C [257]. This process heat has the highest potential in the chemical, refinery, paper, metal, and bioenergy industrial sectors with small capacities (i.e., 50–250 MWth) [258]. Moreover, it can be combined with the (onsite) generated electricity to produce green hydrogen [259]. Depending on the type of the process, the nuclear-based produced hydrogen can be cost-competitive compared to conventional steam reforming, coal gasification, or renewable-based water electrolysis.

We investigated the economic feasibility of nuclear heat or hydrogen cogeneration combined with power generation in Gen III power plants in extra sensitivity analyses. Similar to El-Emam et al. [260], we conclude that the economic feasibility of these technologies primarily depends on the CAPEX. Therefore, as shown in the sensitivity analysis, nuclear cogeneration merely enhances the power system's flexibility and economic feasibility of the investments when nuclear power is cost-effective.

Additional scenario: the low potential of imported biomass, biofuels, and hydrogen

In the nuclear scenario, we assumed a high import potential of critical low-carbon energy sources: biomass, bioethanol, biodiesel, biokerosene, and hydrogen. However, their import potential and price significantly depend on global and regional energy market developments in the coming decades. Therefore, we investigated the impact of lower import capacities of these energy sources on nuclear investments. Thus, we modified the nuclear scenario by fixing the import capacities to 2020 levels.

We find that low biomass and hydrogen import levels increase the need for investments in offshore wind capacity in the short term and nuclear power plants in the long term. In 2030 and 2040, the model builds 11.4 and 14.6 GWe more offshore wind capacity (together with 15.7 and 14.7 GW more offshore transmission line capacity). The extra VRES electricity substitutes the lower biomass and biofuel imports by investing more in high-temperature hybrid boilers and electrolyzers in the short term. Moreover, nuclear investments increase by 0.2 and 1.85 GW in 2040 and 2050. Overall, the lower import levels lead to a substantially higher CO_2 price of 113, 22, and 19%, respectively, in 2030, 2040, and 2050.

Additional scenario: new nuclear investments from 2040 onwards

The country can invest in nuclear from 2030 onwards in the nuclear scenario. It is assumed that nuclear power plants can become available as an off-the-shelf option from international markets (e.g., South Korean reactors). However, licensing and building the nuclear power plant can become moderately lengthy. Therefore, we investigated the implications of allowing new nuclear power capacity available from 2040 onwards.

The results show a 4.4 GW higher need for offshore wind capacity (together with 4.1 GW more offshore transmission line capacity) in 2030, which substitutes the 3 GW nuclear capacity of the nuclear scenario. Moreover, the cost-effective nuclear capacities in 2040 and 2050 vary marginally from the nuclear scenario. Therefore, the exclusion of nuclear power in 2030 leads to slightly lower system costs (i.e., 0.1%) in this period while increasing system costs by 0.4% and 0.3% correspondingly in 2040 and 2050, compared to the nuclear scenario. Therefore, delaying the nuclear investments stimulates higher demand for offshore wind investments in the short term while slightly increasing system costs in the long term.

Additional scenario: higher natural gas prices

In the reference and nuclear scenarios, the imported natural gas price grows moderately to 35 €/MWh in 2050. Since the energy system of the Netherlands in both scenarios still depend on imported natural gas, a higher natural gas price can impact the energy transition. We investigated this impact by assuming higher natural gas price projections from 70 €/MWh in 2030 to 145 €/MWh in 2050. As a result, system costs increased by more than 8% in 2050, 2.8 GWe more nuclear capacity (hitting the maximum 12.48 GW constraint) was built in 2050, and more offshore wind was installed in 2030 and 2040. As expected, the higher imported natural gas prices result in higher dependency on domestic nuclear power and VRES capacities.

6.5. Conclusion

This study sets out to analyze the techno-economic role of nuclear power in reaching national emission reduction targets. Accordingly, we framed this study in four themes: system-wide analyses, cost uncertainties, flexible generation, and cross-border trade. We sourced the IESA-Opt model and modified its methodology to develop the IESA-Opt-N model. The new model has been improved in three aspects: modified objective function in line with system costs definition, more transparent assumptions regarding hourly cross-border electricity trade, and considerably lower computational intensity.

The IESA-Opt-N model offers a suitable approach to analyze the energy system planning because it minimizes the system costs of the national energy system by planning the long-term investments and hourly operation of all energy-related technology options. In addition, the model describes the demand and supply of flexibility (i.e., variations in residual load) for both the energy use and generation sides. Moreover, it includes advanced energy conversion pathways such as green and grey hydrogen, synthetic (gas, kerosene, fuels, and naphtha), and ammonia as a fuel.

By using such a modeling approach, we demonstrated that adopting nuclear power can be cost effective for the Netherlands. However, given all the cost assumption uncertainties (e.g., uncertainties around nuclear construction time, financing, and dismantling costs), the system cost reduction in the nuclear scenario is not significant. Moreover, we analyzed the impact of nuclear power capacity on different sectors of the energy system through several indicators. Additionally, we verified that relying merely on LCOE analyses can underestimate the role of nuclear power in the energy system.

Furthermore, the origin of the capital and the resulting interest rate significantly impact nuclear power's economic feasibility. Under the assumptions of the nuclear scenario, even with a high discount rate of 9 %, nuclear can be economical up to a CAPEX value of 5 B€/GW in 2050. On the other hand, the Netherlands adopts nuclear even in CAPEX values up to 10 B€/GW assuming a low interest rate of 3 %. This outcome is highly relevant to the EU sustainable finance taxonomy since nuclear power has been recently added to the list. Therefore, with governmental support (i.e., low financing discount rates), the relevance of nuclear cost uncertainties on the cost-optimal nuclear power investments is considerably reduced.

Capital expenditure (CAPEX) estimates of variable renewable energy sources (VRES) can moderately affect the cost-optimal nuclear CAPEX range. For instance, with low VRES CAPEX estimates (e.g., wind offshore CAPEX value of 0.85 B€/GW), investments in nuclear power can be cost-effective with nuclear CAPEX below 8 B€/GW. Moreover, under the nuclear scenario assumptions, VRES investments are cost-optimal for the energy system in 2050, irrespective of VRES and nuclear CAPEX estimate levels. Therefore, nuclear power does not substitute the long-term need for high Dutch investments in VRES.

It should be noted that Gen III nuclear power is assumed to operate as a base-load power generator with an exogenous capacity factor of 95 %. Therefore, even in the high availability of VRES, which have low marginal costs, the installed nuclear power capacity has the operational priority at each hour. In these events, the IESA-Opt-N model balances the excess electricity by several means of flexibility supply options such as curtailment, cross-border trade, storage, and demand response.

We demonstrated that the economic feasibility of national nuclear power investments could vary considerably depending on the cross-border electricity trade assumptions. Depending on the cross-border electricity price and available trade volume, nuclear investments follow three primary behaviors: First, with low trade volumes, the model invests in nuclear power to avoid high costs of flexibility supply options. Second, with high trade volumes and high import prices, the model invests in nuclear to avoid high import costs. Third, with high trade volumes and low import prices, the model substitutes nuclear power with cross-border trade volumes.

In addition, we briefly analyzed the role of nuclear cogeneration and other additional scenarios. Nuclear cogeneration can enhance the flexibility and economic feasibility of the investments provided that nuclear power is a cost-effective option. Moreover, low biomass and hydrogen import levels increase the demand for offshore wind capacity in the short term (until it hits the maximum assumed potentials) while increasing nuclear investments in the long term. Additionally, investing in new nuclear power from 2040 onwards (instead of 2030) stimulates higher demand for offshore wind investments in the short term while increasing system costs in the long term. Furthermore, assuming higher imported natural gas prices (i.e., 145 €/MWh by 2050) results in higher short-term investments in VRES and higher long-term investments in nuclear power capacity (i.e., 2.8 GW that hits the maximum 12.48 GW constraint by 2050).

In conclusion, under the cost and trade assumptions of the nuclear scenario, the decision to invest in national nuclear power appears to be cost-optimal according to a high-resolution integrated energy system model. However, the system cost reduction is not considerable considering the cost uncertainties, notably higher financing costs and longer construction time. Moreover, the investments in VRES remain essential for the energy system transition in both scenarios. Therefore, nuclear power can play a complementary role (in parallel to VRES) in achieving Dutch carbon reduction targets. However, the sensitivity analyses show how these results depend on uncertain parameters such as the nuclear CAPEX, discount rate, and cross-border electricity trade. Moreover, the results depend highly on other exogenous assumptions, such as the availability and price of natural gas, biomass, hydrogen, and other imported fuels. The major limitation of this study is that other nuclear-related critical factors are not considered: nuclear waste, social acceptance, energy security, geo-politics of nuclear fuel supply, energy independence, and regional and spatial challenges of building nuclear power reactors.

Soft-linking a national computable general equilibrium model (ThreeME) with a detailed energy system model (IESA-Opt) [49]

Abstract

Top-down CGE models are used to assess the economic impacts of climate change policies. However, these models do not represent the technologies and sources of greenhouse gas emissions as detailed as bottom-up energy system models. Linking a top-down CGE model with a bottom-up energy system model assures macroeconomic consistency while accounting for a detailed representation of energy and emission flows. While there is ample literature regarding the linking process, the corresponding details and underlying assumptions are barely described in detail. The this chapter describes a step-by-step soft-linking process and its underlying assumptions, using the Netherlands as a case study. This soft-linking process increases the Dutch energy demand levels in 2050 by 19.5% on average compared to assumed exogenous levels. Moreover, the GDP in 2050 reduces by 5.5% compared to the baseline economic scenario. Furthermore, we identified high energy prices as the primary cause of this GDP reduction in the soft-linking process.

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7.1. Introduction

Providing an effective climate mitigation policy advice requires insights that take both top-down (TD) and bottom-up (BU) effects of such policies (and their interactions) into account. Such an approach has been used to present an in-depth analysis of global decarbonization scenarios in several studies, such as the climate change report of IPCC AR6 [9], the global energy and climate outlook of JRC [10], and the world energy outlook of IEA [11].

Computable general equilibrium (CGE) models are used to assess top-down effects of climate polices. However, these models oversimplify the energy system and are unable to represent the technological characteristics of the greenhouse gas emission sources. For instance, in CGE models (CGEMs), household energy consumption and emitted emission are often directly related to the household income, whereas in reality, they highly depend on the energy carrier, technology choices, and insulation levels.

CGEMs often represent energy consumption through a simplified and abstract production function where substitution possibilities between energy and capital, as well as between individual energy sources, are modeled assuming a Constant Elasticity of Substitution (CES). Technology is often included in these macroeconomic models as a separate coefficient in the production function. Examples of these models are MERGE [261], CETA [262], DICE [263], and RICE [264]. Some models represent technologies in higher detail by incorporating endogenous technological progress (e.g., DEMETER [265]). Some others reformulated the equilibrium problem as a mixed complementarity problem to represent technologies with higher details [266]. Some integrated assessment models (e.g., FUND[267]) account for energy consumption through economic and environmental parameters such as income, population, and temperature. However, current CGEMs represent far lower technological detail than state-of-the-art BU energy system models.

In contrast, BU energy system models (ESM) provide higher technological, temporal, and spatial details. They include many technological options (e.g., more than 1000) with the corresponding costs, emissions, and physical attributes (e.g., potentials and constraints). Additionally, ESMs can compute on hourly temporal resolution across several regions. However, since ESMs merely compute the partial equilibrium, they are highly dependent on the exogenous general equilibrium state of the system (e.g., energy demand drivers). Consequently, BU models are not capable of performing economy-wide analyses.

Hybrid models can combine the technological explicitness of BU models with the economic richness of TD models through model linking [268]. Various efforts have been made on different energy-economy model linking methods after it was first demonstrated by Hoffman and Jorgenson in 1977 [269]. This allows for improving the analysis: (1) it assures the macroeconomic consistency of the system regarding the aggregate energy demand, inflation, and revenue of agents, (2) it accounts for the indirect effects of the energy transition on the rest of the economy by ensuring the general equilibrium

Hybrid models are classified in several manners. Wene [270] classifies model linking as soft-linking (user controlled) versus hard-linking (computer controlled). Holz et al. [271] divide model linking into three subcategories: 1) soft-linking in which the processing and transfer of information is controlled by the user. 2) hard-linking in which all information processing and transfer is handled by a computer program. 3) integrated modelling in which a unified mathematical approach is used (e.g., applying mixed complementarity problems [266]). Böhringer and Rutherford [268] define three categories: 1) coupling of existing large-scale models (i.e., soft-linking), 2) having one main model complemented with a reduced form of the other, and 3) combining the formulation of the models as mixed complementarity problems. The this chapter adopts the term "soft-linking" as defined by Fragkos and Fragkiadakis [272], where large-scale independently developed TD and BU models are linked through specific variables and an iterative process to ensure convergence. Subsequently, the term "hard-linking" refers to the approach where the TD model (e.g., CGE) is extended to include detailed BU representation (of the energy system).

Each linking approach has its own advantages. Soft-linking requires minimum change to the models. Therefore, the high level of detail of both models can be maintained. However, soft-linking raises several issues, such as the consistency of both models (e.g., data calibration: physical versus monetary flows) and the risk of overlap (e.g., both models define endogenous emissions, energy consumption, and prices). Hard-linking eliminates the consistency problem of soft-linking. However, the level of detail of models is considerably lower than in the soft-linking approach. Since we aim to keep the high level of detail of both models, the this chapter focuses on the soft-linking approach.

The gap between the TD and BU modeling approaches has already discussed three decades ago [273]. Since then, several efforts have combined both approaches in climate mitigation analyses [274]; however, they hardly describe the details and underlying assumptions regarding the linking process. Manne and Wene [275] demonstrate a generic soft-linking approach for the MARKAL and ETA-MACRO models. Wene [270] links the MESSAGE III and ETA-MACRO models by further elaborating connection points. Messner and Schrattenholzer [276] automate the link between MESSAGE and MACRO models. Labriet et al. [277] describe the linking algorithm and convergence criteria in soft-linking two global models, GEMINI-E3 and TIAM. Glynn et al. [278] summarize several model linking efforts for different case studies at national levels. Fortes et al. [279] link the TIMES-PT and GEM-E3 [280] models for the case study of Portugal. Bulavskaya and Reynès [281] investigate the impact of the energy transition on job creation by soft-linking the ETM and ThreeME models. JRC soft-links POLES-JRC [282] and JRC-GEM-E3 [283];

however, since the models have a global perspective, they offer lower detail level compared to national models.

The study by Krook-Riekkola et al. [284] is one of a few that emphasize on soft-linking transparency by describing their linking process and the simulation procedure in detail. They soft-link the TIMES-Sweden [285] and EMEC [286] models and demonstrate the importance of soft-linking in assessing national energy and climate policies.

Due to the growing national policy-driven demand for analyzing socially optimal energy transition pathways [12] and the lack of scientific literature on linking details, there is a need for a transparent national model linking process and its underlying assumptions. Moreover, the detail level of soft-linked models can be improved by using state-of-the-art TD and BU models. However, only a few studies provide transparency on their soft-linking approach.

After identifying several energy system modeling challenges, Fattahi et al. propose the IESA framework [287] to better analyze the transition towards a low-carbon energy system. This framework employs highly detailed models to assess net-zero greenhouse gas (GHG) emission scenarios with high shares of variable renewable energy sources (VRES). For this purpose, the highly detailed and open-source IESA-Opt energy system model is developed [288], calibrated to the Netherlands [289], and its capabilities are tested [290]. Moreover, to address the impact of these scenarios on the economy, the IESA framework suggests soft-linking the core ESM (i.e., IESA-Opt) with a CGEM.

The this chapter aims to provide a transparent soft-linking approach for a highly disaggregated ESM and CGEM at a national scale; and subsequently analyze and demonstrate the relevance of various linking parameters on results, such as energy demand drivers and GDP. In this regard, we choose the IESA-Opt and ThreeME models for their high level of detail in the energy system and economy, respectively. Then, firstly, we demonstrate the soft-linking process of IESA-Opt and ThreeME, its steps, and underlying assumptions. Secondly, we show the impact of soft-linking on model results, particularly energy demand drivers and GDP. Lastly, we quantify the relevance of each soft-linking feedback parameter on the modeling results.

7.2. Methodology

The different underlying methodology of CGEMs and ESMs results in specific advantages and disadvantages for each model. CGEMs describe the whole economy (i.e., general equilibrium) and emphasize the possibility of substituting different production factors in order to maximize the profits of economic agents (e.g., firms, households, and government). However, they considerably lack BU details as they simplify the substitution possibilities between energy and other factors (e.g., capital, labor, and material) using merely the CES production function. Instead, ESMs provide high BU details consisting of many technologies, related costs, physical constraints, potentials, and load profiles, all described in hourly temporal resolution across long-term time horizon and for several regions. However, a weakness of ESMs is that they do not account for general equilibrium effects.

Soft-linking aims to take advantage of both modeling methodologies: the whole economy equilibrium of CGEMs and high BU details of ESMs.

For the soft-linking, we choose ThreeME and IESA-Opt due to their high granularity and state-of-the-art capabilities. ThreeME follows a neo-Keynesian formulation based on a highly disaggregated (65 sectors) economy description. Moreover, its recursive dynamic formulation allows for analyzing the short, mid, and long-term economic shocks as opposed to other CGEMs (e.g., EMEC [286]) that only calculate the initial and last periods. IESA-Opt is a highly detailed energy system model [288] with more than 860 technologies and the corresponding cost and technical data. As opposed to other ESMs (such as TIMES), IESA-Opt features an hourly temporal resolution (in chronological order), which is crucial in modeling scenarios with high shares of VRES.

In the following, we describe further the methodology and level of details of both models. Then, we explain the soft-linking steps and underlying assumptions.

Moreover, in this section, we use specific terms that might have a different definition in each model. In order to increase the clarity, we provide the definition here:

- **Sector** $(\boldsymbol{s})$ is defined in both the energy and macroeconomic models. It refers to a group of activities that share the same or related business activity, product, or service. In Section 7.2.3.2, we modify the sectoral definition of the macroeconomic model to be consistent with the energy model. Each sector is composed of several energy activities.

- **Activity** $(\boldsymbol{a})$ (or activity demand driver) is defined in the energy model. It refers to the energy demand driver, which is an exogenous input to the energy system model. For instance, the steel production industry is considered an activity, which is part of the Basic Metal sector.

- **Commodity** $(\boldsymbol{c})$ is defined in the macroeconomic model. It refers to a basic good that can be interchangeable with other goods in the macroeconomic model. Each commodity can be produced by one or several sectors or be imported. Examples: basic metal, paper, electricity, and oil.

- **Energy carrier** $(\boldsymbol{e})$ is defined in both the energy system and macroeconomic models. It refers to different substances or commodities that are used to carry the energy across the supply-demand chain.

7.2.1. **A brief introduction to the ThreeME model**

Reynès et al. describe the ThreeME model, including all underlying formulations [291]. In short, this CGEM is specifically developed to analyze the impacts of the energy transition on the economy. ThreeME is an open-source country model specially designed to evaluate the medium- and long-term impact of environmental and energy policies at the macroeconomic and sector levels. To do so, ThreeME combines two essential features. Firstly, it has the main characteristics of neo-Keynesian models by assuming a slow adjustment of effective quantities and prices to their notional level, the Taylor rule, and the Phillips curve. Notional level refers to the optimal values that maximize the utility function of each agent (i.e., sectors, household, and government). The Taylor rule is an equation relating the interest rate value to inflation and economic growth levels. The Phillips curve refers to the economic relationship between the rate of unemployment and the rate of change in money wages. Therefore, compared to standard multi-sector CGEMs, ThreeME has the advantage of allowing for under-optimum equilibria, such as the presence of involuntary unemployment. Secondly, ThreeME combines the top-down CGE approach with bottom-up energy models by including several electricity generation technologies.

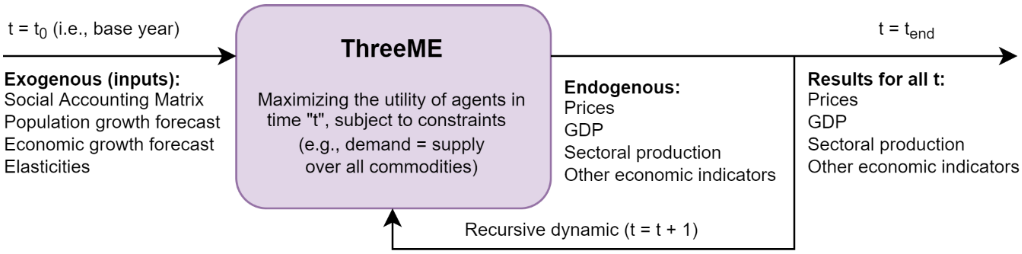

Figure 64. The basic representation of ThreeME and the corresponding inputs and outputs

Figure 64 demonstrates the methodological framework of ThreeME. This model maximizes the utility of each agent in period t subject to several constraints, such as market clearing (e.g., demand is equal to supply). The model is recursive dynamic (i.e., myopic), which means it first optimizes period t and then uses the endogenous results (e.g., prices, wages, and production levels) for optimizing the next period (i.e., $t + 1$). After the model optimizes the last period (determined by the user), it provides the projection of the endogenous parameters, such as prices, household income, GDP, and employment rate, over the whole horizon. Moreover, ThreeME requires several exogenous parameters: the social accounting matrix (SAM) of the base year, population growth forecast, economic growth forecast, and substitution elasticities. SAM is a comprehensive and economy-wide database recording data about all transactions between economic agents in a specific economy for a specific period [292]. The population and economic growth forecasts determine labor availability and productivity projection. Elasticities define the substitution proportion of production factors in production functions.

In a CES function, the substitution between production factors can either follow the linear, fixed-proportion (i.e., Leontief) or Cobb-Douglas production functions. The linear production function represents a production process in which the inputs are perfect substitutes (e.g., labor can be substituted completely with capital). The fixed-proportion production function reflects a production process in which the inputs are required in fixed proportions. In the Cobb-Douglas production function, the inputs can be substituted, if not perfectly. ThreeME assumes a nested CES function [293] to describe the substitution between production factors (Figure 65). This CES production function requires four inputs, KLEM, capital (K), labor (L), energy (E), and material (M). The production factors (KLEM) can be substituted with each other. The Elasticity of Substitution (ES) parameters determines the substitution level between each input. Each pair (i.e., K-E, KE-L, KEL-M) has its own ES, which is explained further in the description of the model [291].

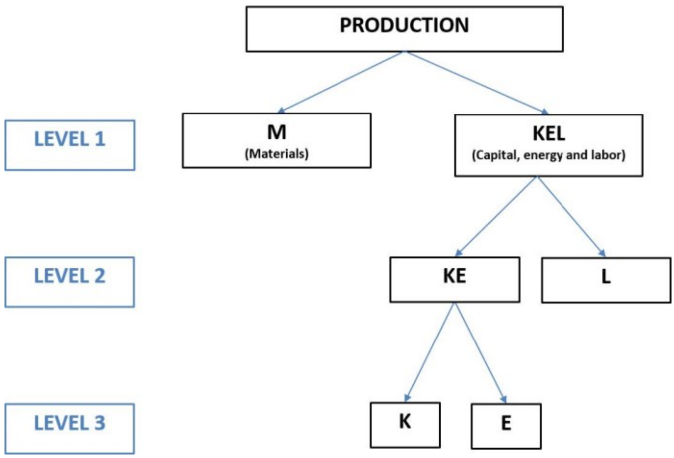

Figure 65. Nested CES production function in ThreeME

An essential characteristic of a standard neo-Keynesian macroeconomic AS-AD (aggregated supply and demand) model is that demand determines supply. The demand comprises (intermediate and final) consumption, investment and export whereas the supply comes from imports and domestic production (see Figure 66). As feedback with eventually some lags, supply affects demand through several mechanisms. The level of production determines the quantity of inputs used by the firms and thus the quantity of their intermediate consumption and investment which are two components of the demand. It determines the level of employment as well and consequently the household final consumption. Another effect of employment on demand goes through the wage setting via the unemployment rate which is also determined by the active population. The active population is mainly determined by exogenous factors such as demography but also by endogenous factors: because of discouraged worker effects, the unemployment rate may affect the labor participation rate and thus the active population.

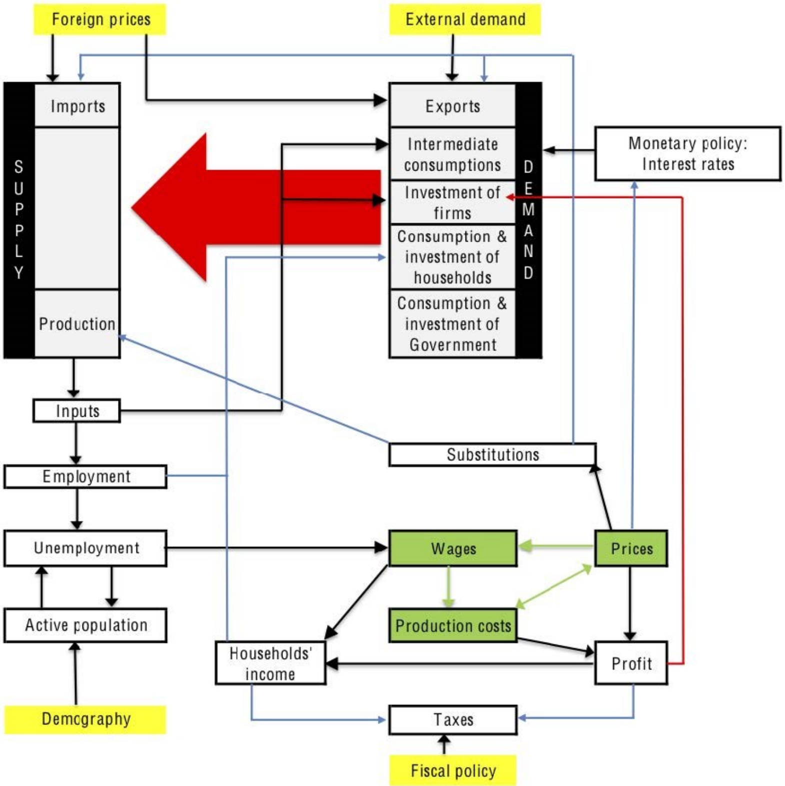

Figure 66. Schematic of the ThreeME model

7.2.2. **A brief introduction to the IESA-Opt model**

IESA-Opt is a detailed open-source optimization ESM at the national level [288]. It optimizes energy system investments over the horizon from 2020 to 2060 in 5-year time steps while simultaneously accounting for hourly and daily operational constraints [289] (see Figure 52). The objective function of the model minimizes the net present value of energy system costs to achieve total energy needs under certain techno-economic and policy constraints (e.g., a specific GHG reduction target in a particular year) [290].

The IESA-Opt model includes a complete sectoral representation of the energy system technologies and infrastructure that account for all greenhouse gas emissions considered in the targets. In addition, it takes into consideration a detailed description of the cross-sectoral flexibility, namely, flexible heat and power cogeneration, demand shedding from power-to-X and electrified industrial processes, short- and long-term storage of diverse energy carriers, smart charging and vehicle-to-grid for electric vehicles, and passive storage of ambiance heat for the built environment. Overall, the model includes more than 860 technologies, with the corresponding capital, variable, and fixed operational cost projections, operational constraints (e.g., availability profile and ramping rate), flexibility constraints (e.g., CHP parameters, demand shedding capacity, pumping loss, demand shifting range), and minimum and maximum deployment potential. Moreover, the energy infrastructure is modeled in nine networks: three different voltage levels of electricity, two different pressures of natural gas, two different pressures of hydrogen, one carbon capture, utilization, and storage (CCUS), and one heat network. While the electricity and heat networks are balanced hourly, the gaseous networks are balanced daily due to their relatively low intraday variation.

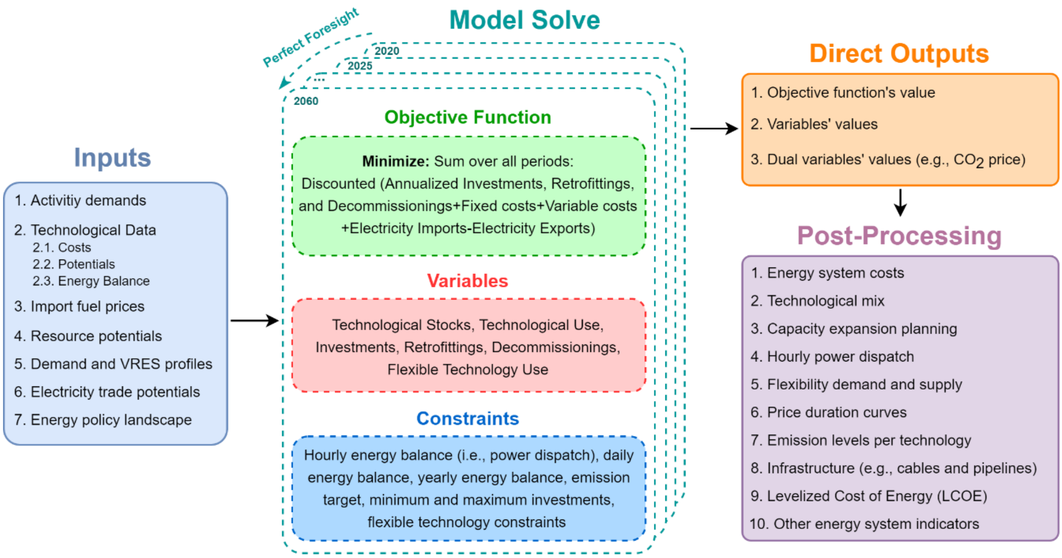

Figure 67. The methodological framework of the IESA-Opt model
Source: [294]

Furthermore, the IESA-Opt model reflects the emission constraints in the EU Emissions Trading System (ETS), the non-ETS sectors, and the international navigation and aviation sectors [295]. Since ETS sector emissions are traded in the EU ETS market, we assume an exogenous ETS emission price projection as a scenario parameter. Because the national emission reduction policy targets both ETS and non-ETS sectors, we set the aggregate national emission constraint on both sectors. If the constraint is binding, the model generates an aggregated national emission shadow price, equal to the marginal increase in the system cost if the aggregated emission constraint gets one unit tighter, e.g., by 1 tonne of CO_2.

The model simultaneously solves multi-year planning of investments, retrofitting, and economical decommissioning with intra-year operational, flexible, and dispatch decisions at hourly temporal resolution. In the present study, the model is applied to the case study of the Netherlands under the current climate policy (which is explained in section 7.3.1) and conservative projections for the economy and availability of resources.

7.2.3. **Soft-linking the IESA-Opt and ThreeME models**

In this section, we describe the soft-linking procedure in three steps. First, we identify the connection points between two models, i.e., which parameters should be linked between two models. Then, we modify the ThreeME model by aligning its sectoral definitions with IESA-Opt definitions and demonstrating the challenges regarding specific connection points of IESA-Opt and ThreeME. Finally, we demonstrate the soft-linking steps and underlying assumptions on feedback parameters between the two models.

7.2.3.1 Identifying connection points

Connection points refer to the shared parameters between two models that can get linked. To identify these points, we review each model's input and output parameters. Figure 64 demonstrates the exogenous inputs of ThreeME as SAM, population and economic growth forecast, and elasticities. Subsequently, ThreeME can provide outputs such as the projection of prices, sectoral production, GDP, and other derived economic indicators (e.g., trade and employment rate). Moreover, the exogenous input of IESA-Opt is described in Figure 52 as the demand drivers for energy consumption (e.g., number of houses, km of transport, tons of steel, and other sectorial activities), technological data, (i.e., costs, potentials, and energy balance), resource potentials and prices, demand and VRES profiles, electricity trade potential, and energy policy landscape. Consequently, IESA-Opt can provide the technological mix, energy mix, energy prices, cross-border energy trade, and other derived energy system parameters.

Linking the outputs and inputs of two models directly can be challenging as the outputs of ThreeME do not exactly match the inputs of IESA-Opt (and vice versa). Moreover, the endogenous parameters of ThreeME are frequently described in monetary units, while IESA-Opt uses both physical and monetary units. Therefore, we need 'translation' models to convert the parameters from one model to the other.

Moreover, all the converted parameters are defined over the period 2020 to 2050. IESA-Opt provides a perfect foresight cost optimized solution over the period 2020 to 2050 with 5-years increments. In contrast, ThreeME myopically simulates the economic general equilibrium with yearly increments from the base year (e.g., 2020) to 2050. Therefore, the exchanged parameters are inherently defined from 2020 to 2050. For instance, by exchanging imported gas prices between two models, we refer to the evolution of the yearly gas price from 2020 until 2050. Since the IESA-Opt model operates in 5-year intervals, we use linear interpolation to estimate the yearly value of parameters.

The proposed method and connection points for soft-linking ThreeME and IESA-Opt are demonstrated in Figure 68. First, we modify the sectoral aggregation level of ThreeME to match IESA-Opt (described further in 7.2.3.2), since both models have different levels of detail and aggregation. For instance, ThreeME describes more than thirty different service sectors, while IESA-Opt assumes merely four technologies to satisfy the aggregated energy demand of the service sector. Then, a demand conversion model links the exogenous energy demand driver parameter of IESA-Opt to the endogenous sectoral production parameter of ThreeME (explained further in section 0). Linking ThreeME to IESA-Opt parameters is more challenging as both models endogenously calculate the energy related parameters. Therefore, we need to modify ThreeME by making the energy related parameters exogenous (i.e., energy and capital productivity, energy mix, energy prices, and cross-border energy trade). Afterwards, an energy mix conversion model links the endogenous energy related parameters of IESA-Opt (i.e., technological mix, energy mix, energy prices, and cross-border energy trade) to corresponding parameters of ThreeME (explained further in section 7.2.3.4). Furthermore, the conversion models should take care of the unit conversion as some of the exchanged parameters have different units.

The exchange of parameters can continue until their values reach the convergence criteria (described in section 7.2.4). In the case of convergence, the outcome of both models consistently describes both the energy system and economy.

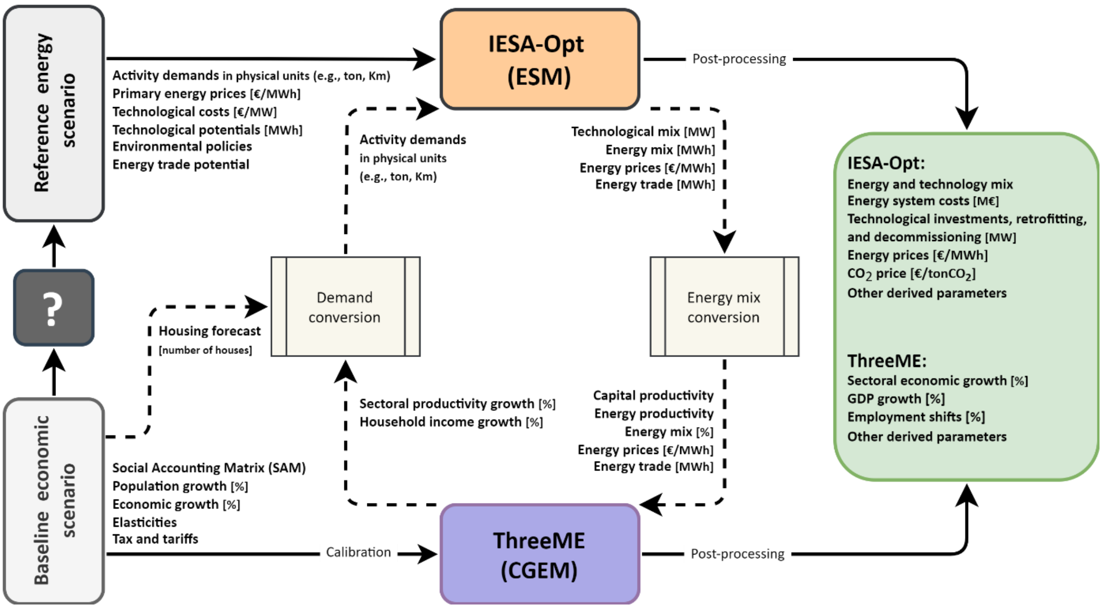

Figure 68. Schematic of soft-linking ThreeME and IESA-Opt.
Soft-linking aims to remove the black box between economic and energy scenarios.
Dashed lines refer to the required data exchange for the soft-linking process.
Solid lines refer to the required data exchange for stand-alone model runs.

The activity demand projections used in energy models generally come from energy outlooks or statistical projections (e.g., Dutch energy outlook [296]). However, the conversion procedure of economic assumptions to energy activities is often not transparent (the gray box in Figure 68). By soft-linking we can improve the consistency of the energy and economic scenarios by aligning the shared input parameters of both models.

7.2.3.2 Modifying ThreeME to IESA-Opt sectoral definition

Often, CGEMs and ESMs represent different definitions of sectors. A CGEM is typically framed around economic sectors. It is calibrated on a Supply Use Table (SUT) as this contains the economic transactions between agents, including firms (i.e., sectors), government, and household. The ThreeME model is calibrated using Eurostat's NACE system of economic activity classifications with 65 economic sectors. Moreover, the energy sector is further disaggregated into 17 energy sectors using the energy balance data. NACE is the acronym[50] used to designate the various statistical classifications of economic activities developed since 1970 in the European Union. NACE provides the framework for collecting and presenting an extensive range of statistical data according to economic activity in the fields of economic statistics (e.g., production, employment, national accounts) and in other statistical domains [297].

Instead, an ESM is usually framed around energy supply and demand sources, and it is calibrated on energy balance statistics. For example, the IESA-Opt model divides the national energy use into five main sectors: built environment (i.e., residential and services), agriculture, industry, transport, and energy conversion sectors. The Dutch database of this model is calibrated using the Dutch 2020 CBS (Central Bureau of Statistics) energy balance reports.

We start the soft-linking procedure by aligning the sectoral definition of two models. In this regard, we aggregate the sectoral definition of ThreeME to match with IESA-Opt. We group the 65 macroeconomic activity sectors into 32 sectors, as shown in Table 59. The left column demonstrates IESA-Opt sectors, while the right column lists modified ThreeME sectors based on the NACE standard.

We were able to connect agriculture, industry, and transport to one another by either directly assigning NACE codes to IESA-Opt sectors or by grouping multiple NACE codes under one sector. For energy conversion, however, we had to use the additional 17 energy sectors in ThreeME, which do not have NACE codes but can still be associated with a NACE sector (e.g. Manufactured gas by C19 relates to C19 - Manufacture of coke and refined

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[50] NACE is derived from the French title “Nomenclature générale des Activités économiques dans les Communautés Européennes” (Statistical classification of economic activities in the European Communities).

petroleum products). Furthermore, the residential and commercial sectors are not compatible as their definitions differ greatly between the two models. Additionally, as ThreeME offers more detailed descriptions of service sectors that are not applicable to IESA-Opt (e.g. J61 - Telecommunications), most of these service sectors have been grouped as the rest of the economy sector.

Table 59. Modified ThreeME sectors based on IESA-Opt sectoral definition
Row colors refer to the IESA-Opt energy sector definition: agriculture, industry, transport, energy conversion sectors.

IESA-Opt sectors	Modified ThreeME sectors
Agriculture	A01 - Crop and animal production, hunting and related service activities; A02 - Forestry and logging; A03 - Fishing and aquaculture
Basic metal	C24 - Manufacture of basic metals
Chemical products	C20 - Manufacture of chemicals and chemical products
Rubber and plastic	C22 - Manufacture of rubber and plastic products
Non-metallic minerals	C23 - Manufacture of other non-metallic mineral products
Paper and board	C17 - Manufacture of paper and paper products
Food products	C10-12 - Manufacture of food products; beverages and tobacco products
Land transport	H49 - Land transport and transport via pipelines; H52 - Warehousing and support activities for transportation; H53 - Postal and courier activities
Navigation	H50 - Water transport
Aviation	H51 - Air transport
Coal production	Solid fossil fuels
Natural gas production	Manufactured gas by C19 (refineries byproduct); Manufactured gas by C24 (basic metal byproduct); extracted natural gas
Natural gas import	Imported natural gas
Biogas production	Manufactured gas by sector D
Crude oil production	Crude oil
Petroleum refining for energy use	C19 - Manufacture of coke and refined petroleum products; Oil and petroleum products (energy)
Petroleum refining for chemical use	Oil and petroleum products (chemical)
Biomass production	Biomass by A02; Biomass by C16 (wood byproduct); Biomass by C20 (chemicals byproduct);
Biofuel production	Manufactured biofuels
Electricity by solid fossil fuels	Electricity production by solid fossil fuels
Electricity by gas	Electricity production by gas
Electricity by petroleum	Electricity production by petroleum
Electricity by hydro	Electricity production by hydro
Electricity by tide, wave, and ocean	Electricity production by tide, wave, and ocean
Electricity by wind	Electricity production by wind
Electricity by solar	Electricity production by solar
Electricity by geothermal	Electricity production by geothermal
Electricity by biomass and biofuels	Electricity production by biomass and biofuels
Electricity by waste	Electricity production by waste
Electricity by nuclear	Electricity production by nuclear
-	Rest of the economic sectors

Table 60. Sectoral demand conversion between CGEM and ESM
Row colors refer to the IESA-Opt energy sector definition: the built environment, agriculture, industry, transport, energy conversion sectors.

ThreeME parameters and variables (Outputs)	IESA-Opt demand parameters (Inputs)
Exogenous CBS housing forecast	Number of houses [Khouses]
	Electricity demand – residential [PJ]
Rest of the economy production growth	Square meter of service space [Mm2]
	Electricity demand – services [PJ]
Agriculture production growth	Electricity demand – Agriculture [PJ]
	Heat demand – Agriculture [PJ]
	Machinery demand – Agriculture [PJ]
Basic metal production growth	Steel production [Mton]
	Aluminum production [Mton]
	Zinc production [Mton]
Chemical production growth	Nitric Acid production [Mton]
	Urea production [Mton]
	Chlorine production [Mton]
	Other Ammonia-based fertilizers [Mton]
	Other ETS chemicals [Idx_2020]
Rubber and plastic production growth	Ethylene production [Mton]
	Propylene production [Mton]
	Other HVC products [Mton]
Non-metallic production growth	Glass production [Mton]
	Ceramics production [Mton]
Paper and board production growth	Paper and board production [Mton]
Food production growth	Food production [Idx_2020]
Refined products exports growth	Naphtha [PJ]
	Road fuel [PJ]
	Kerosene [PJ]
	Fuel oil [PJ]
	Other oil products [PJ]
Other industry production growth	Other ETS industry [Idx_2020]
	Other non-ETS industry [Idx_2020]
Households' income growth, fuel price growth	Motorcycles [Gvkm]
	Passenger cars [Gvkm]
Land transport production growth	Light-duty vehicles [Gvkm]
	Heavy-duty vehicles [Gvkm]
	Buses [Mvkm]
	Rail [Mvkm]
Water transport production growth	Domestic navigation [Mvkm]
	International navigation [Mvkm]
Households' income growth, fuel price growth	Intra-EU aviation [Mvkm]
	Extra-EU aviation [Mvkm]
Production in energy commodities	Endogenous

7.2.3.3 Demand conversion (From ThreeME to IESA-Opt)

Soft-linking practices often skip explaining their demand conversion procedure in detail. However, studies such as Krook-Riekkola et al. [284] demonstrate their sectoral demand conversion parameters and corresponding units. Inspired by their study, we demonstrate our method to convert ThreeME variables into IESA-Opt energy demand drivers.

The sectoral demand conversion parameters for soft-linking IESA-Opt and ThreeME are demonstrated in Table 60. For most sectors, since we already aligned both models' sectoral definitions, we can directly connect the required energy demand drivers of IESA-Opt to the sectoral production growth out of ThreeME:

$$D_{a,t^*,n+1} = D_{a,t_b}.\left(\prod_{t_b}^{t^*} \alpha_s.PrG_{s,t,n}\right)$$

Where $D_{a,t^*,n+1}$ is the demand of activity a, in time t^*, iteration $n+1$, exogenous input to IESA-Opt; $D_{a,t}$ is the demand of activity a, in the base year t_b, in IESA-Opt calibration; α_s is the demand conversion factor of sector s; and $PrG_{s,t,n}$ is the gross production growth of sector s, in time t, iteration n, and endogenous output from ThreeME. The demand conversion factor (β_s) determines the correlation between physical production growth (used in the energy model) and the monetary sectoral growth (used in the economy model). The value of this parameter, which can be obtained by correlating historic data, hardly deviates from one in the case of Sweden [284]. Therefore, in this study we assume this factor to be equal to one to increase the clarity of the linking procedure.

Not all activity demand drivers of IESA-Opt can be linked to ThreeME through the mentioned formula, namely, the number of houses and the amount of vehicle kilometers of passenger cars and motorcycles. For instance, the number of houses (exogenous input to IESA-Opt) depends more on the demography and housing policies of the country rather than economic growth or governmental income (output of ThreeME).

The residential heat demand is determined endogenously in IESA-Opt. This model requires the number of houses and heat degree days as inputs to optimize the cost-effective insulation level of houses and corresponding heat supply technologies. For the number of houses, we assume the projection forecasts of CBS [298], which is in line with the assumed demography projections of ThreeME. Similarly, the services heat demand is determined endogenously. IESA-Opt requires the amount of square meter service space and heat degree days as inputs to calculate the cost-effective insulation level and heat supply technologies. However, unlike the residential sector, we can assume that the office space demand follows the economic growth of the services sector.

Moreover, IESA-Opt requires the vehicle km demand as an exogenous input. Estimating the transport demand projections is rather a complex task that depends on several factors such as household income, fuel price, population densities, public transport availability, and roads congestion levels [299]. However, transport projection can be estimated by the variations in income and fuel price [300]:

$$TD_{t^*,n+1} = TD_{t_b}.\left(\prod_{t_b}^{t^*} HIG_{t,n}\right)^{\varepsilon_{HI}}.\left(\prod_{t_b}^{t^*} FPG_{t,n}\right)^{\varepsilon_{FP}}$$

Where $TD_{t^*,n}$ is the transport demand in time t^*, iteration $n+1$, and exogenous input to IESA-Opt; $HIG_{t,n}$ is the households' income growth in time t, iteration n, and endogenous output of ThreeME; ε_{HI} is the elasticity of transport demand to households' income; $FPG_{t,n}$ is the fuel price growth in time t, iteration n, and endogenous output of ThreeME; and ε_{FP} is the elasticity of transport demand to fuel price. The choices of long-term ε_{HI} and ε_{FP} elasticities usually come from historic econometrics analyses that can vary significantly: $0.65 \leq \varepsilon_{HI} \leq 1.25$ and $-0.55 \leq \varepsilon_{FP} \leq -0.05$ [301]. We choose the subjective values of $\varepsilon_{HI} = 1.2$ and $\varepsilon_{FP} = -0.3$ for the elasticities. Moreover, since passenger car fuel mix changes to electricity over time, we use a weighted average fuel cost based on the endogenous gasoline and electricity prices of IESA-Opt. For the aviation, we use the endogenous kerosene price calculated by IESA-Opt.

7.2.3.4 Energy conversion (From IESA-Opt to ThreeME)

This section describes the underlying assumptions of reflecting IESA-Opt outputs on the ThreeME model. Here we link four parameters, namely, technological mix, energy efficiency, energy mix, and energy prices. Moreover, in each subsection, we explain the required modification in ThreeME to take the mentioned energy-related parameters as exogenous parameters.

Technological mix

The optimal technological mix (from a cost perspective) to satisfy a specific energy activity might differ significantly under different scenarios. For instance, to satisfy a particular demand for electricity, the energy model optimally invests in, e.g., coal power plants or wind turbines. Since the cost of these technological options can vary greatly, it can greatly affect the monetary flow of the economy. Under tight environmental policies, some monetary flows (e.g., coal power plants) might disappear, and new substitutes (e.g., wind turbines) appear. This variation can affect the rest of the economy, such as employment and trade levels. We can trace this effect on different parts of the economy (e.g., sectoral employment and trade levels) by converting the technological mix into an appropriate input for the CGEM.

The variation in the technological mix required to satisfy a specific sectoral activity affects the capital productivity of the corresponding sector. An increase in the technological cost of a specific sector can be interpreted as a decrease in the capital (K) productivity in the corresponding sector. Therefore, compared to the base year, variations in technological costs in IESA-Opt translate into variations in sectoral capital productivity in the ThreeME model:

$$Prod_{s,t,n+1}^{K} = Prod_{s,t_b}^{K}.\beta_s.\left(\frac{WAC_{a,t_b}}{WAC_{a,t,n}}\right)$$

Where $Prod_{s,t,n+1}^{K}$ is the capital (K) productivity of sector s, in time t, iteration $n+1$, and exogenous input to ThreeME; $Prod_{s,t_b}^{K}$ is the capital productivity of sector s, in the base year t_b, and exogenous input to ThreeME; β_s is the ratio of energy capital costs over sectoral capital costs of sector s, and exogenous from historic data; $WAC_{a,t,n}$ is the weighted average cost of activity a, in time t, iteration n, and endogenous output of IESA-Opt; and WAC_{a,t_b} is the weighted average cost of activity a, in the base year t_b, in IESA-Opt calibration. In ThreeME, $Prod_{s,t,n}^{K}$ is an exogenous value, which usually is assumed equal to its value in the base year (i.e., $Prod_{s,t_b}^{K}$). However, we modify ThreeME to take this parameter as an exogenous value with the mentioned formulation. Moreover, in this study we assume $\beta_s = 1$; thus, any variation in energy capital costs implies changes in the sectoral capital costs.

Energy efficiency

The change in the technological mix and energy efficiency from IESA-Opt affects the sectoral energy productivity factor in ThreeME. From the energy model perspective, energy efficiency occurs in two ways: (1) exogenous increased efficiency of single technology due to technological development, and (2) endogenous substitution of technologies resulting in lower energy demand to satisfy the same activity. Similarly, in ThreeME, (1) the exogenous energy productivity factors determine the production levels based on consumed energy, and (2) the exogenous substitution elasticities together with endogenous prices determine the substitutions in the energy mix. In this section, we suggest a link for the first measure of efficiency, while in the next sub-section (i.e., energy mix) we connect the second energy efficiency measure.

With an increase in energy efficiency, the energy productivity should increase, meaning that less energy is required to reach the same amount of production. The variations in energy efficiency can translate into energy productivity by:

$$Prod_{s,t,n+1}^{E} = Prod_{s,t_b}^{E}.\left(\frac{EU_{a,t_b}}{AL_{a,t_b}} \Big/ \frac{EU_{a,t,n}}{AL_{a,t,n}}\right)$$

Where $Prod_{s,t,n+1}^{E}$ is the energy (E) productivity of sector s, in time t, iteration $n+1$, and exogenous input to ThreeME; $Prod_{s,t_b}^{E}$ is the energy productivity of sector s, in the base year t_b, and exogenous input of ThreeME; $EU_{a,t,n}$ is the energy use of activity a, in time t, iteration n, and endogenous output of IESA-Opt; $AL_{a,t,n}$ is the activity level of activity a, in time t, iteration n, and exogenous input to IESA-Opt (which is based on an endogenous output of ThreeME in iteration n); EU_{a,t_b} is the energy use of activity a, in the base year t, and endogenous output of IESA-Opt calibration; and AL_{a,t_b} is the activity level of activity

a, in the base year t, and exogenous input to IESA-Opt. Similar to $Prod^{K}_{s,t,n+1}$ parameter, in ThreeME, $Prod^{E}_{s,t,n+1}$ is an exogenous value, which is usually equal to $Prod^{E}_{s,t_b}$. However, we modify ThreeME to take this parameter as an exogenous value with the mentioned formulation.

Energy mix

ThreeME assumes exogenous elasticities of import, export, and energy use to endogenously determine the share of import, export, and energy mix based on the price difference. However, these shares can be replaced by the energy trade and energy mix outcomes from the IESA-Opt model. Therefore, we modify the energy production factor of ThreeME by assuming substitution elasticity of zero (i.e., the so-called Leontief production function). Thus, modified ThreeME takes energy shares exogenously:

$$\varphi_{e,c,s,t,n+1} = {EU_{e,a,t,n}}\Big/{\sum_e EU_{e,a,t,n}}$$

Where $\varphi_{e,c,s,t,n+1}$ is the share $\left(\sum_e \varphi_{e,c,s,t,n} = 1\right)$ of energy carrier e in producing commodity c, in sector s, in time t, iteration n, in the ThreeME model; $EU_{e,a,t,n}$ is the energy use of activity a, from energy carrier e, in time t, iteration n, from IESA-Opt; and $\sum_e EU_{e,a,t,n}$ is the summation of all energy use of activity a, in time t, iteration n, from IESA-Opt.

Energy prices

Except for the price of imported energy carriers (that is exogenously equal for both models), other energy prices are endogenously determined in both models. However, IESA-Opt provides more accurate energy prices (i.e., shadow prices) as it includes rich details of the energy system's interactions and constraints. For example, the hourly shadow prices of electricity network are used to determine the average yearly price, which is then imposed into ThreeME.

Originally, ThreeME calculates the price mark-up based on the price elasticity of demand, which is an exogenous parameter. Since the prices in ThreeME are endogenous variables, we modify them to be equal to energy price values from IESA-Opt. Therefore, we alter the energy commodity price formula by removing the mark-up:

$$P_{e,t,n+1} = P_{GDP,t,n}.YAP_{e,t,n}$$

Where $P_{e,t,n+1}$ is the energy price of energy carrier e, in time t, iteration $n+1$, and exogenous input to ThreeME; $P_{GDP,t,n}$ is the GDP price (i.e., inflation correction factor), in time t, iteration n, and endogenous output of ThreeME; and $YAP_{e,t,n}$ is the yearly average price of energy carrier e, in time t, iteration n, and endogenous output of IESA-Opt.

7.2.4. **Execution**

The applied steps of the soft-linking process are summarized in Figure 69. Since the activity demands are the required inputs of IESA-Opt, we choose ThreeME as the starting point. First, the sectoral production output of ThreeME is converted into energy demand drivers through the demand conversion model (explained in section 0). Then, we run IESA-Opt based on the acquired energy demand drivers. Next, the energy-related outputs of IESA-Opt are converted into required inputs of ThreeME through the energy conversion model (explained in section 7.2.3.4). At this point, we increase the iteration index by one and repeat the iteration. Finally, the process stops when the energy demand drivers are converged according to the convergence criterion. Once the process is converged, we can report the outcomes of both models with the highest iteration index as the final results.

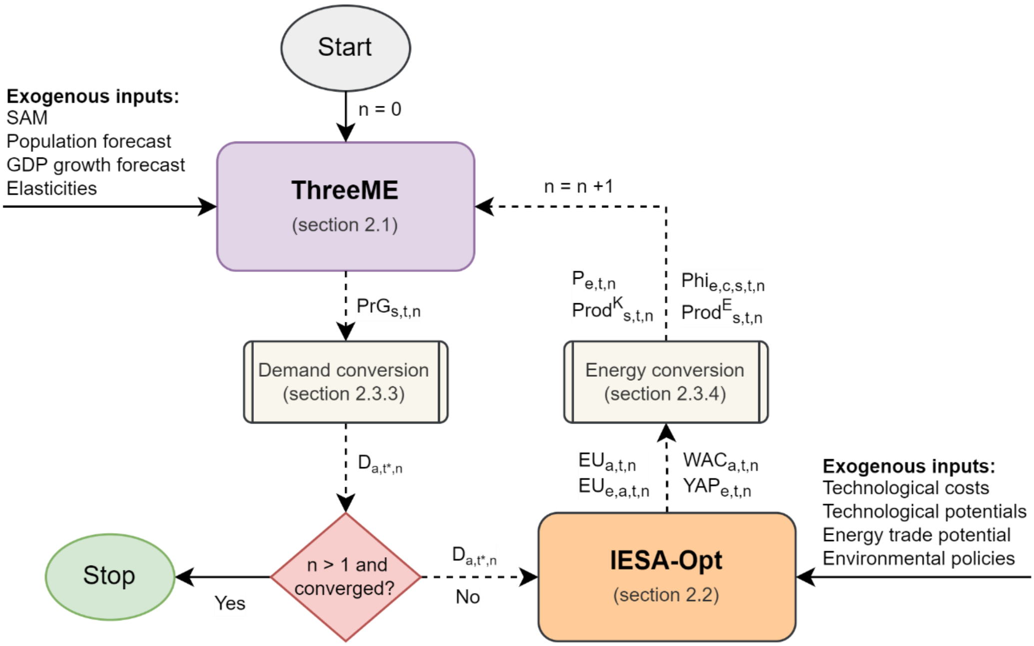

Figure 69. The execution flowchart of the iterative soft-linking process
Dashed lines refer to the iterative soft-linking process

Depending on the linking level and iteration index, we define several stages: First, the stand-alone (SA) stage, which refers to the activity values obtained exogenously as described in the reference scenario section 7.3.1. At this stage, there is no link between the two models. Second, the no-feedback (NF) stage is the one-way linking of ThreeME outputs into IESA-Opt. In this stage, the energy activity demands are reported at iteration 0 just before the red diamond in Figure 69. Third, the feedback loop (FL) stage in which the soft-linked ThreeME and IESA-Opt exchange data in iterations (i) until reaching the convergence criterion. Table 61 summarizes the soft-linking stages.

Table 61. The soft-linking stages and the corresponding execution steps

Stages	n-value	Description
SA	NA	Exogenous input to the stand-alone IESA-Opt model
NF	0	ThreeME → Demand conversion
FL-1	1	ThreeME → Demand conversion → IESA-Opt → Energy conversion → ThreeME → Demand conversion
FL- i	i	Repeating the iterations i times

Moreover, there is a need to determine convergence or stop criteria that determine when the iterations should stop. Some studies set predefined convergence criteria (e.g., the differences in energy consumption per energy carrier and calibrated sector are less than 10% [279]), and some others set no convergence criteria and decide when to stop after analyzing the outcome of each iteration [284]. Since the only impact of ThreeME on IESA-Opt in this soft-linking process is through the variation in energy demand drivers, we set the convergence criterion as:

$$\left|\frac{D_{a,t^*,n} - D_{a,t^*,n-1}}{D_{a,t^*,n-1}}\right| \leq 1\% \quad \forall s, t \ \ and \ \ n > 1$$

Where the absolute variations in demand drivers for all sectors and times between two iterations are less than 1%.

7.3. Applying the soft-linking procedure

This section primarily has two goals: First, analyzing the impact of soft-linking on the modeling results, and second, quantifying the relevance of feedback parameters between two models. Therefore, the choice of the scenario parameters is of secondary importance. However, we summarize the main characteristics of this scenario.

7.3.1. **Reference scenario**

For the IESA-Opt model, except the number of houses that is obtained from CBS, the projected development of other activities and part of the resource costs are extracted from the Dutch national energy outlook (KEV) [296] and JRC's POTEnCIA central scenario for the Netherlands [154], which is based on GDP growth rates presented in the 2018 aging report [155]. s scenario leans towards business-as-usual economic development, which would fall within the second shared socioeconomic pathway (SSP2) [156]. Moreover, the environmental policy landscape of the Netherlands follows the EU Green Deal [218], where the Netherlands steps up its ambition to reduce its greenhouse gas (GHG) emissions by 55% compared to 1990 levels in 2030, and becomes GHG neutral in 2050.

For the ThreeME model, the SAM of the Netherlands in 2015 is obtained from the National Accounts datasets of Eurostat [302]. Moreover, the population and GDP growth forecasts are obtained from the Dutch statistical agency (CBS).

Table 62. The assumed GDP growth and population forecasts of the reference scenario in both models.

		2020	2030	2040	2050
GDP growth [%]	IESA-Opt	1.4	1.1	1.5	1.8
	ThreeME	1.5	1.5	1.5	1.5
Population [million]	IESA-Opt	17.5	18.4	19.1	19.2
	ThreeME	17.4	18.5	19.0	19.3

Although both models use a separate source of GDP and population forecasts, the assumed values are not considerably different (see Table 62). IESA-Opt data sources assume a GDP growth of 1.45% (from 2020 to 2050), while ThreeME assumes a constant 1.5% growth.

7.3.2. **Impact of soft-linking on the outcomes**

7.3.2.1 Sectoral development

Figure 70 demonstrates the activity demand levels of main Dutch industrial sectors in 2050 during different linking stages. The soft-linking approach increases the activity demand levels by 30.4% on average compared to the stand-alone IESA-Opt assumptions. The first increase in the NF stage is primarily due to the economic growth assumptions of ThreeME. Thus, it does not reflect any feedback from IESA-Opt. However, considering the first feedback from IESA-Opt (i.e., FL1), the activity demand levels reduce by 10.8% on average compared to the NF stage. The reason for this decrease is described further in section 7.3.3. After FL1, the average reduction in activity demand levels is negligible (2.7% from FL1 to FL2 and 0.03% from FL2 to FL3). In total, compared to the SA stage (i.e., stand-alone IESA-Opt without linking), soft-linking increases the activity demand levels by 19.5% on average.

The presence of a significant gap demonstrates the discrepancy between exogenous sources and the ThreeME outcome, due to the varying assumptions made. Utilizing exogenous demand levels makes the results heavily reliant on a number of assumptions that are challenging to evaluate. Soft-linking enhances the transparency and traceability of demand side assumptions, guaranteeing a general economic equilibrium that is in line with the energy-climate policy.

The increase in activity demand levels varies across different sectors: from approximately 40% in basic metals to roughly 5% in food products. Due to the lack of information on the assumptions of exogenous sources, we can hardly trace the reasoning behind this variation.

In this case study, the soft-linking procedure meets the convergence criterion after three iterations. However, the activity demands of 2050 already reach significant convergence in the first iteration (i.e., FL1 stage). In a similar study, the soft-linking procedure reached significant convergence after the first iteration [284]. Moreover, other sectors behave similarly through the iterations except for the passenger car and aviation sectors. The reason is that these sectors follow a different energy demand conversion formulation dependent on household income and fuel prices.

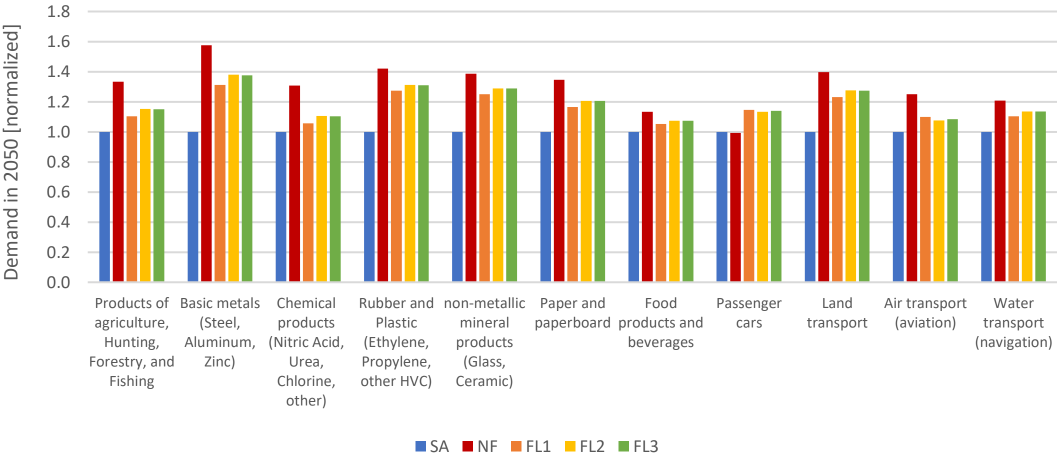

Figure 70. Energy demand activities of IESA-Opt normalized to the SA stage. SA: Stand-Alone IESA-Opt, NF: No Feedback from IESA-Opt to ThreeME, FLi: Feedback Loop between two models (i.e., two-way soft-linking) at the iteration i.

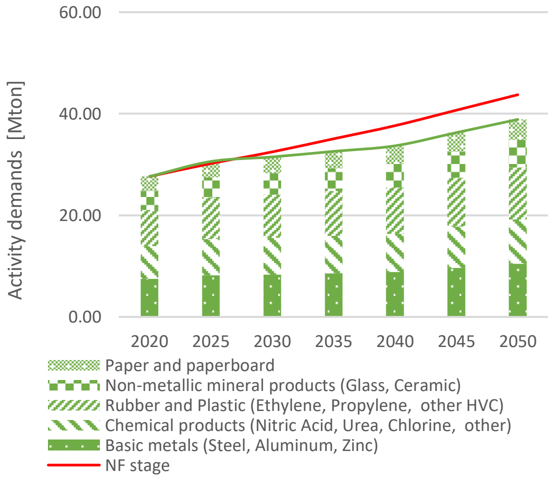

Figure 71. Energy activity demand projections of the primary industrial sectors of the Netherlands in the third iteration (i.e., the FL3 step)

The projection of activities in the last iteration (i.e., the FL3 step) does not grow linearly as assumed in the reference economic scenario (see the NF stage in Figure 71). Compared to the assumed linear production growth in ThreeME, the soft-linked production growth hampers in 2030, mainly due to lower export levels that can be explained by higher energy costs. In the reference scenario, ThreeME assumes a constant 2% increase in prices (both domestic and international commodities) to account for the inflation. However, the energy prices of IESA-Opt (i.e., shadow prices) are calculated as the marginal cost of the technologies that satisfy the energy demand in each period. Therefore, enforcing ThreeME to use IESA-Opt energy prices causes considerable price disparity between energy-intensive products and the rest of the products.

For instance, for the steel production sector in 2030, IESA-Opt decommissions the current blast furnace technology and instead invests in the direct reduction from hydrogen technology. While blast furnace technology mainly requires coal, the latter primarily relies on hydrogen and electricity. Moreover, as the output of IESA-Opt, the price of electricity and hydrogen should increase considerably in 2030 to reach the 55% GHG emission reduction policy. As a result, the weighted average energy price for steel production increases by 270% from 2020 (coal-based) to 2030 (hydrogen and electricity-based). This price upsurge increases the price of steel commodity by 44% from 2020 to 2030. In contrast, in the same period, the international price of steel increases merely by 22% (i.e., 2% growth per year). Figure 72 demonstrates that the steel price surges from 2030 to 2035, resulting in the lower competitiveness of domestic steel compared to the international market. Accordingly, ThreeME lowers the growth of exported steel between 2030 and 2035 (see Figure 73), consequently decreasing the need for domestic steel production.

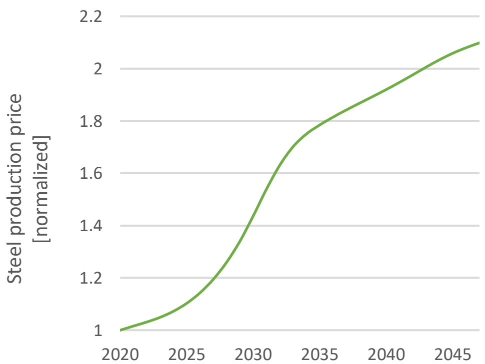

Figure 72. Steel commodity price normalized to 2020. This price is endogenously calculated in ThreeME based on the imported energy prices from IESA-Opt.

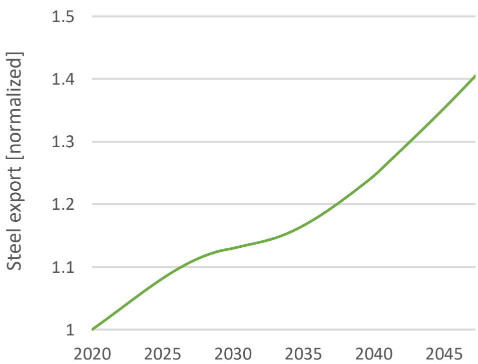

Figure 73. The export projection of the steel commodity according to ThreeME and normalized to 2020.

Not all sectors experience a production reduction in the energy transition. For example, Figure 74 demonstrates the projections of passenger car and aviation sectors before and after soft-linking (i.e., in the NF and FL3 stages). As we assumed in section 0, the passenger car and aviation transport demands are correlated positively with household income and negatively with fuel prices. Thus, both sectors grow steadily in the NF stage as part of the reference economic scenario. However, after soft-linking, the demand of each sector follows a different pathway.

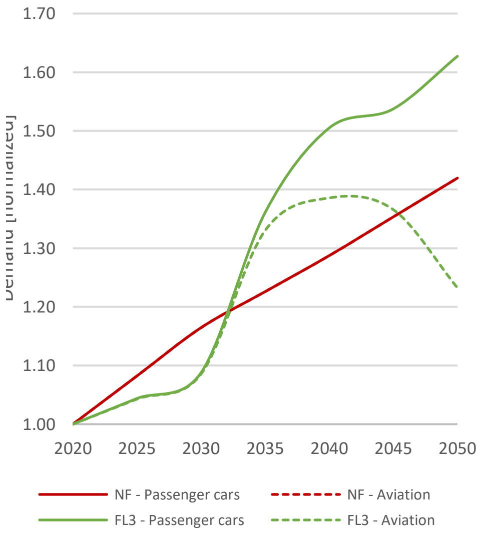

Figure 74. Passenger car and aviation demand projections in the NF and FL3 stages. The values are normalized to 2020 levels.

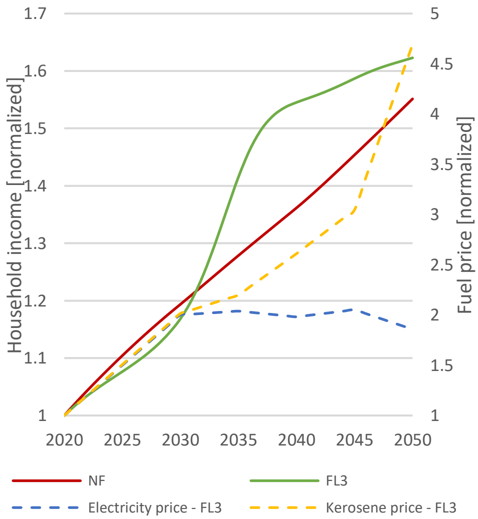

Figure 75. The household income and fuel price projections in the NF and FL3 stages. The values are normalized to 2020 levels.

The passenger car demand curve follows an s-curve that decreases in 2025 and increases considerably after 2035 compared to the NF line. The main driver for this behavior is the variation in household income (see Figure 75) that follows an s-curve. Additionally, the passenger car fuel price (i.e., electricity) stays almost steady from 2030 to 2045. In 2050, the electricity price reduces by 9% compared to 2045, which further boosts the 2050 passenger car demand (see Figure 74).

The aviation demand follows a similar pattern until 2035 but falls considerably until 2050. From 2035 onwards, household income continues to increase; however, as shown in Figure 75, the kerosene price increases at a noticeably faster rate (e.g., 80% increase from 2040 to 2050) due to the stringent net-zero climate policy in 2050. Therefore, the projected aviation demand reduces by 11% from 2040 to 2050 (see Figure 74).

7.3.2.2 The economy

Figure 76 shows the variations in GDP during the different stages of the soft-linking. GDP is an aggregate measure of production equal to the sum of the gross added values of all resident institutional units engaged in production (plus any taxes and minus any subsidies) [303].

In the FL3 stage, considering the feedback of IESA-Opt (i.e., capital and energy productivity, energy mix, energy prices, and cross-border energy trade), the GDP decreases by an average of 5.5 % compared to the NF stage (i.e., baseline economic scenario). Since the assumed GDP growth of both models are similar (see Section 7.3.1), the main part of this decrease is due to the considerable impact of the IESA-Opt feedback parameters in the first iteration. After the FL1 stage, the variation in the GDP trend is hardly affected by the number of iterations between the two models.

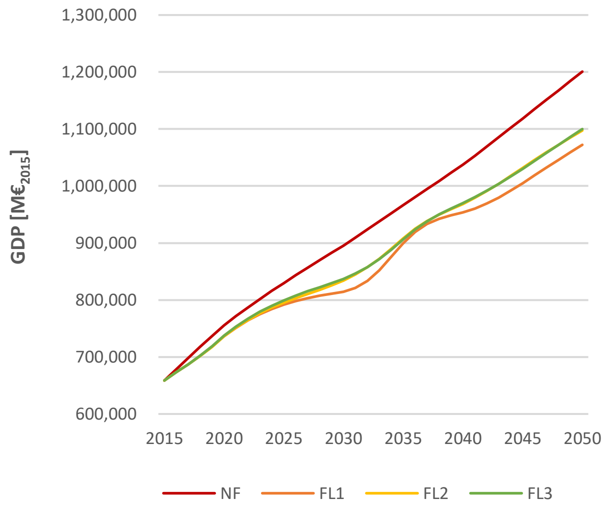

Figure 76. Variations in the GDP during different steps of soft-linking. NF: No Feedback from IESA-Opt to ThreeME, FLi: Feedback Loop between two models (i.e., two-way soft-linking) at iteration i.

The decrease in economic activity is mainly driven by the decrease in exports (-12.3% in 2050, see Figure 77), whereas the decreases in investment and consumption are relatively small compared to the NF stage. This trade balance deterioration is driven by the increase in the domestic price of energy commodities and thus sectoral commodities (as explained in section 7.3.2.1). The increase in prices leads to the lower international competitiveness of domestic products starting from 2030 to 2040 (assuming a business-as-usual scenario in the rest of the world). After 2040, the IESA-Opt energy prices do not change considerably, and international commodity prices continue to increase at the constant rate of 2% (as assumed in the reference scenario). Therefore, the reduction in exports remains and starts to decrease slightly as the difference between domestic and international prices decreases.

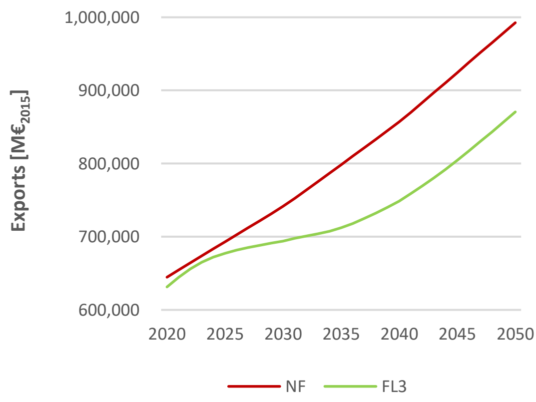

Figure 77. The projection of exports in the NF and FL3 stages (i.e., before and after soft-linking).

7.3.3. **The relevance of feedback parameters**

The presented soft-linking approach consists of two directions: demand conversion and energy mix conversion. While the demand conversion contains only the energy demand parameter, the energy mix conversion involves four parameters: productivity factors, energy mix, energy prices, and energy trade.

This section demonstrates the impact of soft-linking these parameters on the energy demand drivers. This impact is compared at six levels: no feedback from IESA-Opt to ThreeME, feeding back only productivity factors, only energy mix, only energy prices, only energy trade, and complete feedback (i.e., soft-linked).

The impact of feedback parameters on the primary Dutch industrial demands in 2050 is presented in Figure 78. First, the energy mix feedback increases the demand levels by 1% on average in all sectors compared to the no-feedback stage. The higher endogenous electrification rate (the output of IESA-Opt) stimulates sectoral production as there will be less demand for fossil energy commodity imports.

Second, feeding back the capital and energy productivity factors reduces energy demand drivers by merely 0.4% compared to the NF stage. While the energy productivity increases in all sectors (due to higher efficiency), the capital productivity increases in some sectors (e.g., basic metals) and reduces in others (e.g., paper and paperboard). For instance, in the basic metals sector, IESA-Opt invests in the hydrogen direct reduction process, which is assumed to be slightly cheaper and more efficient than blast furnaces. This leads to an increase in capital and energy productivity, resulting in lower demand for capital and energy - consequently, 0.8% higher steel production.

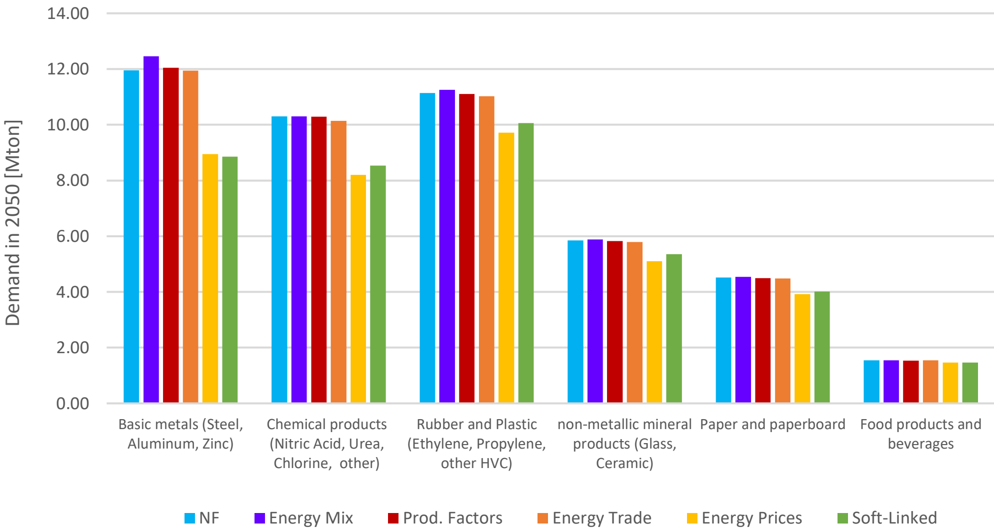

Figure 78. The variations of primary Dutch industrial demands in 2050 with respect to soft-linking feedback stages. NF: No feedback from IESA-Opt to ThreeME, feeding back only energy mix, only productivity factors, only energy prices, only energy trade, and full feedback (i.e., soft-linked).

Third, the energy trade feedback reduces the sectoral demand by 0.9% compared to the NF stage. The primary reason for this minimal impact is the assumption of constant energy commodity exports (except electricity) from 2020 onwards. Consequently, the energy import volumes that IESA-Opt determines endogenously do not change considerably compared to the base year. Therefore, by assuming drastic changes in energy trade volumes in the long term, we expect that the impact of this feedback parameter will become more prominent.

Fourth, the energy commodity prices are the primary feedback parameter with a 15% average decrease in the energy activity drivers compared to the NF stage. The higher energy prices increase the production costs and thus domestic commodity prices (as explained in section 7.3.2.1). Since domestic commodities become more expensive compared to the NF stage, and ThreeME assumes a constant growth of international prices from the base year, the competitiveness of domestic products reduces (depending on the assumed export elasticity). As a result of reduced exports, the production levels reduce drastically. Therefore, the impact of this parameter on the final results depends primarily on the IESA-Opt energy prices and assumed growth of international prices and trade elasticity.

In summary, the energy commodity price feedback has the highest impact on the final results compared to other feedback parameters. However, the magnitude of this feedback depends on specific modeling assumptions both in the economy and energy models.

7.4. Discussion

Although the demonstrated soft-linking approach ensures the economic equilibrium of the energy system, it comes with several assumptions that can affect the results (summarized in Table 63). Here we briefly discuss the key assumptions and their potential impact on the outcomes.

Table 63. The list of main soft-linking assumptions and issues to be resolved

Assumption/issue	**Resolution**
Sectoral definition matching	Is challenging. A more detailed CGEM is required
Novel value chains	Need for forward-looking CGEM
Linking investment costs	Soft-link capital costs where necessary
Differences between the energy and economic capital costs	The impact on results is not considerable
Perfect foresight as opposed to the myopic methodology	Proposing a modification in ThreeME
Convergence criterion	We should monitor the process, not only the criterion
Demand-elasticity in ESMs	Can be used when soft-linking is out of reach
Importance of elasticities and the base year choice	Sensitivity analyses are required
Relevance of international trade	Global CGEM or sensitivity analyses are required
Price linking method	Further investigation is required
Assumed energy price projections	Alternative scenario analysis is required
Further analyzing the economic results	In-depth economic analysis is required

Sectoral definition matching

Table 59 and Table 60 clearly show how the sectoral definition matching between the two models is established. However, this is can be highly critical and difficult to carry out since it either may interrupt the logic of one of the models or disturb the relation between data sources and models sectors. In this study, we used energy and economy models with high sectoral resolution and with the ability of grouping sectors. For example, sectors can get merged in ThreeME to match IESA-Opt sectors. Therefore, matching their sectoral definitions raised minimal challenges.

In the proposed soft-linking process, the IESA-Opt energy demand drivers are calculated based on endogenous ThreeME sectoral growth. Although we aligned the sectoral definition of ThreeME to IESA-Opt, still the linking can be improved. For instance, the growth in the land transport sector determines the growth in the light and heavy-duty vehicles, busses, and trains in IESA-Opt. However, the demand for busses and trains is not necessarily determined by the land transport sector growth. Increasing the sectoral disaggregation of ThreeME could resolve this issue. For instance, EMEC [284] provides greater sectoral detail by distinguishing between public transport, road freight, and rail transport sectors.

Novel value chains

In this study, a CGE model based on historic data, such as SAM and elasticities, was utilized. However, due to its reliance on existing data, it is unable to accurately reflect novel production value chains like green hydrogen, synthetic fuels, DAC, and BECCS that do not yet have a significant impact on the economy. One approach would be assuming these value chains behave similar to current economic commodities (e.g., green hydrogen can be treated as natural gas). However, in order to be more accurate, these production value chains and their associated elasticities must be added to the CGE model.

Linking investment costs

In the present study we linked the investment costs of two models because an investment in a capital-intensive technology resulting from ESM can affect the capital intensity of the corresponding sector in CGEM, and hence, the economic equilibrium. Although some other studies such as Krook-Riekkola et al. [284] did not include linking investment costs in their soft-linking approach, they mentioned this issue as a shortcoming of their approach.

Even though we showed that the impact of this linking parameter is not considerable on the results, we advise including this linking parameter for sectors in which the ratio of capital over variable costs can shift considerably during the course of energy transition. An example is the transport sector where the ratio of capital over variable costs for electric cars is noticeably higher than conventional cars.

Differences between the energy and economic capital costs

We are assuming the energy model capital costs represent the whole capital costs of the sector ($\beta_s = 1$). However, this is not the case in reality, as an energy-related capital cost of a specific sector only represents a share of its total investment costs. We can analyze the historical data to identify the energy-related capital cost-share of each sector. This share can be used as a sectoral elasticity in section 7.2.3.4 to calculate the $Prod_{s,t,n}^{K}$ more accurately. Although we have demonstrated that the impact of linking the capital factor on the results is not significant, we suggest calibrating the β_s values from the base year. Moreover, in a similar study [284], β_s values for the Swedish economy are extracted; however, the reported values do not differ considerably from 1, which was used in this study. Therefore, we do not expect considerable change in the results if real β_s values are used.

Perfect foresight as opposed to the myopic methodology

Although the underlying methodologies of both models are different, there is one major difference that can cause inconsistency between two models. On the one hand, in the IESA-Opt model, the objective function (i.e., energy system costs) is minimized with perfect foresight to provide a socially optimal energy transition pathway. On the other hand, the ThreeME model simulates a general equilibrium between several economic agents (e.g., households and government) with myopic foresight. Thus, these economic agents only apply adaptive expectations with backward-looking under bounded rationality. As a result, the investment decisions in IESA-Opt look ahead, while their effect in ThreeME has a myopic impact. Similarly, this inconsistency between the two models is briefly recognized by Fortes et al. [279] as GEM-E3 [280] is a recursive dynamic model while TIMES [108] has perfect foresight.

To diminish this inconsistency, we propose defining a social objective function in ThreeME that optimizes a specific variable over the trajectory. In this way, the model can employ future information to reach a perfect foresight equilibrium iteratively.

Convergence criterion

There are other candidates for the convergence criteria. Fortes et al. [279] use the criterion that the variation in energy consumption per energy carrier between iterations should be lower than 10% or 1 PJ. Another criterion is used by Labriet et al. [277] in which the average relative difference between the energy demand driver values obtained at two successive iterations should be smaller than a sufficiently small threshold. The this chapter uses the energy demand driver as the primary convergence criterion because it is essential for the IESA-Opt results. However, we should not merely rely on a convergence criterion; besides, we need to administer the linked parameters at each stage to ensure meaningful linking as Krook-Riekkola et al. [284] suggested.

Demand-elasticity in ESMs

ESMs such as the TIMES model family have the capability of implementing demand-elasticities, which allow for changes in demand due to endogenous commodity prices or substitution elasticities. This approach can help with demand adjustments in response to changes in prices, but is not an adequate substitution for soft-linking. Soft-linking ensures that economic equilibrium is kept in line with the energy policy set by the ESM, which demand-elasticities are not capable of doing. On the other hand, demand-elasticities have the advantage of not requiring the time and effort that soft-linking does, thus the choice between the two depends on the objectives and capabilities of the research team.

Importance of elasticities and the base year choice

CGEM results highly depend on the assumed elasticities. The variation in economic behavior can lead to variations in elasticities, which can highly affect the results. For instance, a robust national willingness to reduce energy imports can lower substitution elasticity between domestic and imported energy commodities. In this study, we merely used default elasticities. However, there is room to investigate the role of variations in elasticities in the final results. For instance, as was shown in the results section, trade elasticity plays a crucial role in determining the competitiveness of domestic products and thus economic growth. Moreover, the energy system transition can considerably impact these elasticities in long-term (e.g., 2050).

Moreover, the choice of the base year determines the starting point of the economy. Therefore, we suggest choosing a "good" starting year that represents the economy the best. For instance, choosing 2020 as the base year might underestimate the economic growth as it was under the temporary impact of the covid-19 pandemic. Moreover, the chosen base year should be near enough to represent the most recent state of the economy. Therefore, we choose 2015 as the base year in the present study. However, we suggest using the more recent "good" base year given the corresponding SAM is available.

Relevance of international trade

ThreeME assumes a steady-state increase in international energy and commodity prices. However, this assumption is far from reality as the international price of commodities can change considerably based on different national policies, notably climate policies. For instance, domestic climate policies increase energy prices and, consequently, sectoral commodity prices. Thus, domestic commodities become less competitive in the international market, which results in lower exports and consequently lower domestic GDP growth. Therefore, the assumed growth of international commodity prices can drastically affect the impact of energy policies on economic growth.

This issue can be addressed in two ways: first, performing a sensitivity analysis of the results by assuming several exogenous international commodity price projections. Second, use a global CGEM to account for international trade. The second method, however, comes at the cost of reduced domestic modeling details as global CGEMs are considerably more aggregated than national ones.

Price linking method

In ThreeME, the commodity price is endogenously defined as a mark-up over costs. In the this chapter, we assumed that the IESA-Opt energy commodity prices (i.e., shadow prices) are passed directly to ThreeME. Therefore, a higher energy price simulated by IESA-Opt corresponds implicitly to a higher mark-up. However, it could also have been modeled through an increase in input cost, in particular the one of capital. Similarly, Krook-Riekkola et al. [284] faced challenges in linking prices.

The price linking assumption impacts the generated incomes, their beneficiaries, and thus, the overall economic impact. Therefore, different methods of price linking and their impact on the results need further investigation.

Assumed energy price projections

The reference scenario used in the present study does not consider the recent high levels of fossil fuel prices, particularly in Europe, which are caused by the disrupted supply of natural gas and oil. However, the assumed energy price projections play an essential role in the results, as it was shown in the results.

With higher fossil fuel prices, low-carbon energy sources become more cost-effective. Therefore, the commodities made using low-carbon energy become cheaper than fossil fuel-based commodities. Therefore, with higher international fossil fuel prices, we expect the relative competitiveness of domestic commodities to increase since the share of low-carbon energy is expected to increase considerably in the Netherlands. This effect can be quantified with the proposed method in the this chapter; however, it falls out of the scope of this study.

Further analyzing the economic results

The present study merely analyzes the aggregated economic indicators such as the export and GDP levels. However, the relevance of soft-linking on more detailed economic indicators was not discussed. Therefore, there is a need for an in-depth analysis of the results that would require looking at additional economic indicators, decomposing economic impacts (in particular between substitution effects and income effects), and sensitivity analysis of critical parameters (e.g., elasticities) of the model. Since these in-depth economic analyses falls out of the scope of this study, we keep that for further research.

7.5. Conclusion

The present study aims at providing a transparent soft-linking approach for highly disaggregated computable general equilibrium model (CGEM) and energy system model (ESM) at the national scale; and subsequently analyze and demonstrate the relevance of various linking parameters on results, such as energy demand drivers and GDP.

Compared to the stand-alone IESA-Opt (without linking), the soft-linking increases the activity demand levels of 2050 by 19.5% on average. This outcome is particularly significant for ESM modelers, as they often use the exogenous energy demand drivers from external sources. Furthermore, this outcome shows that the assumed exogenous energy demand drivers of ESMs are not necessarily consistent with the expected economic growth. Therefore, soft-linking can bridge this gap by ensuring general economic equilibrium instead of partial equilibrium in ESMs. However, we should ensure that novel production value chains (resulting from ESMs) are captured properly in CGEs. For instance, green hydrogen is expected to play a major role in achieving net-zero emission targets; however, its production value chain is not properly modeled in CGE models that rely on historic SAM and elasticities.

Moreover, in the first soft-linking iteration, the energy demand drivers in 2050 reduced by 10.8% on average compared to the no-feedback (NF) stage, in which IESA-Opt outputs are not fed into ThreeME. We showed that this reduction in energy demand drivers led to a 5.5% reduction in GDP. This outcome is particularly relevant to CGE modelers as they often oversimplify the energy system and its impact on the economy. Therefore, soft-linking can improve the CGEM results by accounting for ESM feedbacks that emerge from analyzing climate policies with rich bottom-up details.

Furthermore, we demonstrated that in this case study, the energy prices parameter is the primary feedback among four feedback parameters: productivity factors, energy mix, energy prices, and energy trade. The energy prices parameter reduces the energy activity drivers in 2050 by 15% on average compared to the NF stage. We illustrated that the energy prices of IESA-Opt increase the production cost of ThreeME commodities and consequently reduce the international competitiveness of domestic products. Therefore, high energy prices (resulting from IESA-Opt) decrease the exports, and thus, GDP and energy demand drivers. This outcome elevates the significance of international trade assumptions or the need for a global economy model while modeling a national energy-economy linked system.

In addition, as explained in the discussion section, the proposed soft-linking method and analyses can be improved in several ways, such as performing sensitivity analyses on primary scenario parameters (e.g., elasticities), using a global CGEM or an international scenario framework, increasing the sectoral detail of ThreeME, improving the price linking between models, providing in-depth economic analyses, and analyze the results considering high fossil fuel price projections.

Although there exist other studies that provide a transparent soft-linking methods for national models, the present study improves the literature by increasing the transparency level and quantifying the relevance of the feedback parameters in the utilized approach. Each soft-linking effort requires making particular assumptions depending on the underlying methodology and resolution of the used models. Therefore, comparing the results of soft-linking approaches would be challenging. However, readers can benefit from the higher transparency and diversity of approaches, and employ a mixed approach that is best suited for their study.

Summary and Conclusions

Energy System Models (ESMs) have been developed to guide decision-makers in making long-term robust policy decisions toward low-carbon energy system transition. However, many ESMs lack specific capabilities for adequately addressing this transition. This lack of capabilities affects the quality of the national energy transition scenarios. This thesis aimed to improve national energy system modeling capabilities and demonstrate its impact on Dutch energy transition scenarios.

I started by identifying energy system modeling gaps by taking into consideration expected elements of energy transition. This includes greatly increased use of low-carbon energy sources (such as wind, solar, geothermal, and nuclear power) and new energy carriers (e.g., hydrogen, ammonia, and synthetic fuels). To make the best use of these energy sources we must implement sector coupling (e.g. Power to Heat (P2Heat), Power to Mobility (P2Mobility), Power to Liquids (P2Liquids), and Power to Gas (P2Gas)), storage solutions (e.g. batteries, seasonal thermal energy storage (TES), and compressed air energy storage (CAES)), and demand-side management (e.g. demand response and demand shedding). Furthermore, smarter infrastructure management (such as collective heat networks, smart power distribution, and hydrogen pipelines), and increased social involvement (through prosumers and decentralized generation) must be put in place. Moreover, it is crucial that the entire carbon balance is considered, including energy and non-energy related emissions (such as enteric fermentation, fertilizers, and manure management) and carbon removal schemes, such as, afforestation, bioenergy carbon capture and storage (BECCS), and direct air capture (DAC). In addition, this transition can have a major impact on the whole economy as capital and labor flows are redirected toward the elements mentioned.

Then, based on policy needs and the identified gaps, I proposed a conceptual modeling suite, IESA, to bridge major energy system modeling gaps. Moreover, together with Manuel Sanchez, we developed a state-of-the-art optimization ESM, IESA-Opt, to better model the energy system transition of the Netherlands. Further, I demonstrated the impact of higher modeling capabilities on national energy transition policies, for instance, the role of nuclear power. Finally, to cover the macroeconomic impacts of the energy transition, I closed the IESA suite by soft-linking IESA-Opt and an advanced computable general equilibrium model, namely, ThreeME.

Furthermore, we provided an open-source and user-friendly ESM with a corresponding database that lowers the entry barrier to the energy system modeling field. Moreover, I designed and implemented an interactive online user interface to present model results. Furthermore, we collaborated with the ENSYSTRA project by co-developing the IESA-NS model. The developed tools and software in the present research have provided insights and enabled several other researchers and Ph.D. and master students to conduct their research effectively. The result of the general approach that was presented in the Introduction section is presented in Figure 79.

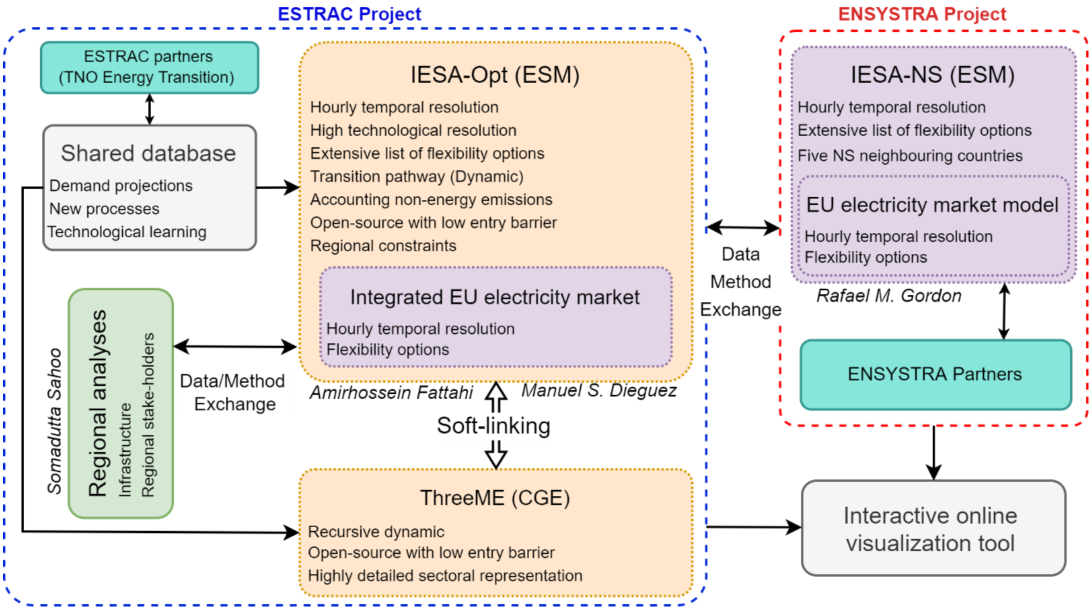

Figure 79. The result of the general approach of this study
Box colors: Lime: Regional scale; Orange: National scale; Purple: Transnational scale; Cyan: Project partners

The main contributions and outcomes of the present dissertation can be summarized:

1. We developed a state-of-the-art integrated energy system framework (i.e., IESA).
2. I demonstrated the impact of advanced modeling capabilities on Dutch energy transition scenarios.

3. Using the IESA framework, I linked energy system analysis with macroeconomics and policy.
4. We laid a novel energy system modeling framework with a low entry barrier.
5. I showed that an efficient use of computational capacity and a lean methodology could open doors to analyses that were left unexplored.

In the following, first, I provide a summary of chapters in Section 8. Then, I summarize the research outcomes and answers to research questions (Section 8.2). Afterwards, in Section 8.3, I reflect on the research's main findings by providing overall conclusions and recommendations.

In this thesis, chapters 3 and 4 are the outcome of a joint effort with Manuel Sanchez Dieguez, the other PhD colleague in the ESTRAC project. The rest of the thesis is mainly the outcome of my efforts with the input of co-authors. In the following, the pronoun "we" refers to co-authors of each chapter.

8.1. Summary of chapters

Chapter 2: A systemic approach to analyze integrated energy system modeling tools, a review of national models

In this chapter, we reviewed academic literature focusing on nineteen integrated Energy System Models (ESMs) to (i) identify the capabilities and shortcomings of current ESMs to analyze adequately the transition towards a low-carbon energy system, (ii) assess the performance of the selected models by means of some derived criteria, and (iii) discuss briefly some potential solutions to address the ESM gaps.

We found that, it is not a practical conclusion to decide on the best model that addresses challenges regarding low-carbon energy systems, as each model has specific pros and cons. From a techno-economic point of view, our review indicates that for modeling the low-carbon energy system, current models require specific capabilities such as hourly temporal resolution, regional spatial resolution, inclusion of sectoral coupling technologies, technological learning, and inclusion of social parameters. There are major gaps between policy questions and modeling capabilities in the criteria which were used to assess the models' performance. However, these criteria mainly focus on the technical policy questions rather than the entire technical, microeconomic, and macroeconomic aspects. Although techno-economic models are rich in detail, they lack the capability to answer microeconomic and macroeconomic policy questions. Therefore, specific models, such as energy market models and general equilibrium models, have been developed. Due to the strong interconnection between energy and economy, mixed policy questions arise that require analyzing the technical, microeconomic, and macroeconomic aspects of the energy-economy system. Such analysis can be conducted either by developing single models or combining different models (e.g., soft-linking).

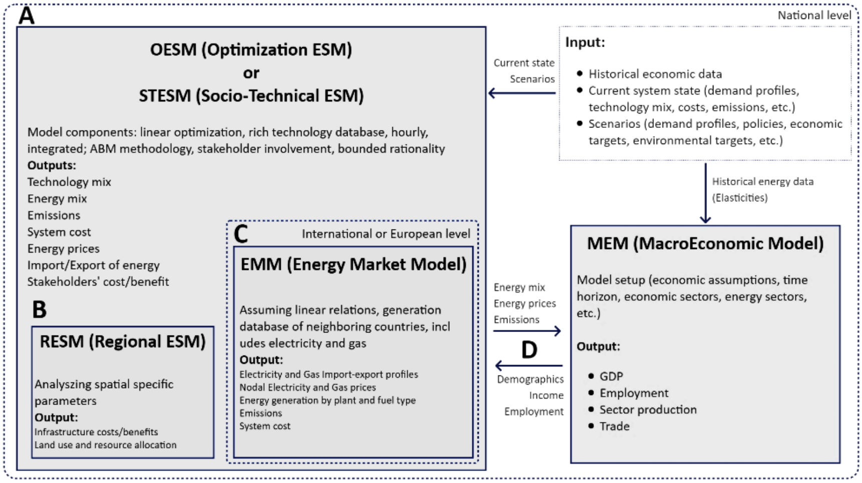

Figure 80. Optimization-based or Simulation-based conceptual model linking framework for the IESA energy system modeling suite

A linking approach is proposed (Figure 80) for addressing current energy system modeling gaps. This linking can form a modeling suite that involves four models, namely, the Energy System Model (ESM), the Energy Market Model (EMM), the Macroeconomic Model (MEM), and the Socio-Spatial Model (SSM). The core ESM can be formed around either an Optimization ESM (OESM) or Socio-Technical ESM (STESM) model. While OESM provides the cost-optimal state of the energy system assuming a fully rational central social welfare planner, STESM demonstrates a more realistic state of the energy system by assuming profit maximizer agents who consider social decision-making parameters, such as behavioral economics, bounded rationality, neighborhood effect, and technology diffusion curve, in their decision-making process.

Chapter 3: Linear programing formulation of a high temporal and technological resolution integrated energy system model for the energy transition

This chapter describes the underlying formulation of the IESA-opt model. IESA-Opt is an optimization model using a linear programming (LP) formulation to determine the cost-optimal investment path in the transition towards 2050 decarbonization targets and the operation of the technologies present in the system. An LP approach allows for representing the energy system with high sectoral, technological, and temporal resolution while maintaining computational feasibility. The chosen formulation also allows for the flexible framework used in the model, which enables the energy system to be described in clusters or to include geographical constraints of the model. Conventional large-scale, long-term planning energy system models frequently use LP methodology to avoid excessive computational loads. Due to their narrower system scope, operational energy system models, especially power system models, employ a mixed-integer linear programming (MILP) methodology to account for binary or integer variables such as investment and unit-commitment decisions. The choice of LP over MILP methodology can considerably reduce the computational time without important deviations in the results, especially in energy systems with high shares of VRES. The computational time of the LP formulation can be significantly lower than that of the MILP approach (up to 100 times) while providing relatively high precision in modelling relevant flexibility options. The most significant modelling sacrifice of not using a MILP approach is that the concept of economies of scale cannot be represented through convex functions. However, the latter downside is counterweighted by the higher resolution of the activities considered by the model, which allows for different policy guiding approaches. Unfortunately, adequate testing of this hypothesis would require a contrasting MILP formulation that cannot be feasibly solved for such a large problem at reasonable times without the need for supercomputers.

Chapter 4: Modelling of decarbonisation transition in national integrated energy system with hourly operational resolution

IESA-Opt is an adequate tool for analyzing the impact of cross-sectoral flexibility in an integrated energy system in the Netherlands, which helps in understanding ways to further accommodate large amounts of variable renewable electricity. As evidence of this, IESA-Opt was applied in this case study to determine the behavior of energy system transition when taking into consideration interactions in terms of energy usage, emissions, and costs, while considering intra-year dynamics of the dispatch and operation of the power dispatch, gaseous networks, and cross-sectoral flexibility. Following are the two most relevant highlights of these results: 1) even in a high decarbonization scenario, fossil fuels remain largely used as many causal factors such as international transport, exports of refined products, and industrial feedstock are not included in current climate policies in the Netherlands; 2) there will be a pivotal switch from fuel costs to capital costs in the energy transition that is mainly driven by electrification and the adoption of "fuel-less" renewable energy sources and technologies that can provide cross-sectoral flexibility.

In addition, several sensitivity analyses were performed to highlight the critical role of biomass and CCUS in achieving negative emissions to highlight the importance of including different demand streams for oil in the climate policy packages and to quantify the uncertainty of key demand volumes for different sectors. From these, the most significant learning is that in order to displace oil-based products from the energy mix, a policy package comprising international transport, feedstock for high-value chemicals, and refined oil products exports is required in top of the current emission reduction targets. However, to make this transition affordable and effective it is necessary to ensure the availability of biomass resources together with the development of carbon capture and storage technologies. These findings are very relevant to help guiding the energy transition and are worthy to further exploration by means of further expansion of IESA-Opt capabilities as well as by the linking of the model with other analytical tools.

Chapter 5: Measuring accuracy and computational capacity trade-offs in an hourly integrated energy system model

In this chapter, we quantified some modeling trade-offs by employing an applied energy system model that covers all energy sectors, includes grid infrastructure, and integrates a transnational linear power system representation that includes cross-border trade. We generated 21 cases based on a reference scenario of the Netherlands as a case study, while the results can be interpreted for other similar national energy systems. We measured the cost of increasing resolution in each modeling capability in terms of computational time and energy system modeling indicators, notably, system costs, emission prices, electricity generation, and import and export levels.

Our findings can be summarized as: First, reducing the transitional scope from seven to two periods can reduce the computational time by 75% while underestimating the objective function by only 4.6%. Second, if the electricity trade with each neighboring country is not the focus of the study, modelers can assume a single EU node that dispatches electricity at an aggregated level (while still describing the distribution of the technologies taking part in the dispatch). This assumption underestimates the objective function by 1% while halving the computational time. Furthermore, shedding technologies (such as electrolysers) and storage options are a must for any integrated energy system with high shares of variable renewable energy, as their absence can strongly affect modeling outcomes in terms of the objective function, system configuration, and operation of technologies. In general, neglecting flexibility options can drastically decrease the computational time but can increase the sub-optimality by up to 31%. Finally, while reducing the computational time to half, the lack of electricity and gas infrastructure representation can underestimate the objective function by 4% and 6%, respectively.

This chapter comes with some shortcomings. For instance, we assumed flat profile for a considerable number of technology options, while hourly load profiles can play an important role in determining the optimal portfolio of technologies. Acquiring hourly load profiles for each technology and energy source (e.g., wind and sun) can be a challenge. Therefore, modelers may assume the same profile for a set of technologies or use clustering methods in data preprocessing. It is highly suggested to analyze the impact of input data resolution on modeling results and computational loads.

This chapter can guide energy system modelers to better frame their modeling assumptions based on the focus of their study. The quantified modeling trade-offs presented in this chapter, can be used by other energy system modelers to better identify crucial computational gaps. Moreover, energy modelers can realize the quantified importance of analyzed modelling capabilities on accuracy of results.

Chapter 6: Analyzing the techno-economic role of nuclear power in the Dutch net-zero energy system transition

This chapter sets out to analyze the techno-economic role of nuclear power in reaching national emission reduction targets. Accordingly, we framed this chapter in four themes: system-wide analyses, cost uncertainties, flexible generation, and cross-border trade.

By using the IESA-Opt modeling approach, we demonstrated that adopting nuclear power can be cost effective for the Netherlands. However, given all the cost assumption uncertainties (e.g., uncertainties around nuclear construction time, financing, and dismantling costs), the system cost reduction in the nuclear scenario is not significant. Moreover, we analyzed the impact of nuclear power capacity on different sectors of the energy system through several indicators. Additionally, we verified that relying merely on LCOE analyses can underestimate the role of nuclear power in the energy system.

Furthermore, the origin of the capital and the resulting interest rate significantly impact nuclear power's economic feasibility. Under the assumptions of the nuclear scenario, even with a high discount rate of 9 %, nuclear can be economical up to a CAPEX value of 5 B€/GW in 2050. On the other hand, the Netherlands adopts nuclear even in CAPEX values up to 10 B€/GW assuming a low interest rate of 3 %. This outcome is highly relevant to the EU sustainable finance taxonomy since nuclear power has been recently added to the list. Therefore, with governmental support (i.e., low financing discount rates), the relevance of nuclear cost uncertainties on the cost-optimal nuclear power investments is considerably reduced.

Capital expenditure (CAPEX) estimates of variable renewable energy sources (VRES) can moderately affect the cost-optimal nuclear CAPEX range. For instance, with low VRES CAPEX estimates (e.g., wind offshore CAPEX value of 0.85 B€/GW), investments in nuclear power can be cost-effective with nuclear CAPEX below 8 B€/GW. Moreover, under the nuclear scenario assumptions, VRES investments are cost-optimal for the energy system in 2050, irrespective of VRES and nuclear CAPEX estimate levels. Therefore, nuclear power does not substitute the long-term need for high Dutch investments in VRES.

It should be noted that Gen III nuclear power is assumed to operate as a base-load power generator with an exogenous capacity factor of 95 %. Therefore, even in the high availability of VRES, which have low marginal costs, the installed nuclear power capacity has the operational priority at each hour. In these events, the IESA-Opt-N model balances the excess electricity by several means of flexibility supply options such as curtailment, cross-border trade, storage, and demand response.

We demonstrated that the economic feasibility of national nuclear power investments could vary considerably depending on the cross-border electricity trade assumptions. Depending on the cross-border electricity price and available trade volume, nuclear investments follow three primary behaviors: First, with low trade volumes, the model invests in nuclear power to avoid high costs of flexibility supply options. Second, with high trade volumes and high import prices, the model invests in nuclear to avoid high import costs. Third, with high trade volumes and low import prices, the model substitutes nuclear power with cross-border trade volumes.

In addition, we briefly analyzed the role of nuclear cogeneration and other additional scenarios. Nuclear cogeneration can enhance the flexibility and economic feasibility of the investments provided that nuclear power is a cost-effective option. Moreover, low biomass and hydrogen import levels increase the demand for offshore wind capacity in the short term (until it hits the maximum assumed potentials) while increasing nuclear investments in the long term. Additionally, investing in new nuclear power from 2040 onwards (instead of 2030) stimulates higher demand for offshore wind investments in the short term while increasing system costs in the long term. Furthermore, assuming higher imported natural gas prices (i.e., 145 €/MWh by 2050) results in higher short-term investments in VRES and higher long-term investments in nuclear power capacity (i.e., 2.8 GW that hits the maximum 12.48 GW constraint by 2050).

In conclusion, under the cost and trade assumptions of the nuclear scenario, the decision to invest in national nuclear power appears to be cost-optimal according to a high-resolution integrated energy system model. However, the system cost reduction is not considerable considering the cost uncertainties, notably higher financing costs and longer construction time. Moreover, the investments in VRES remain essential for the energy system transition in both scenarios. Therefore, nuclear power can play a complementary role (in parallel to VRES) in achieving Dutch carbon reduction targets. However, the sensitivity analyses show how these results depend on uncertain parameters such as the nuclear CAPEX, discount rate, and cross-border electricity trade. Moreover, the results depend highly on other exogenous assumptions, such as the availability and price of natural gas, biomass, hydrogen, and other imported fuels. The major limitation of this chapter is that other nuclear-related critical factors are not considered: nuclear waste, social acceptance, energy security, geo-politics of nuclear fuel supply, energy independence, and regional and spatial challenges of building nuclear power reactors.

Chapter 7: Soft-linking a national computable general equilibrium model (ThreeME) with a detailed energy system model (IESA-Opt)

This chapter aims at providing a transparent soft-linking approach for highly disaggregated computable general equilibrium model (CGEM) and energy system model (ESM) at the national scale; and subsequently analyze and demonstrate the relevance of various linking parameters on results, such as energy demand drivers and GDP.

Compared to the stand-alone IESA-Opt (without linking), the soft-linking increases the activity demand levels of 2050 by 19.5% on average. This outcome is particularly significant for ESM modelers, as they often use the exogenous energy demand drivers from external sources. Furthermore, this outcome shows that the assumed exogenous energy demand drivers of ESMs are not necessarily consistent with the expected economic growth. Therefore, soft-linking can bridge this gap by ensuring general economic equilibrium instead of partial equilibrium in ESMs. However, we should ensure that novel production value chains (resulting from ESMs) are captured properly in CGEs. For instance, green hydrogen is expected to play a major role in achieving net-zero emission targets; however, its production value chain is not properly modeled in CGE models that rely on historic SAM and elasticities.

Moreover, in the first soft-linking iteration, the energy demand drivers in 2050 reduced by 10.8% on average compared to the no-feedback (NF) stage, in which IESA-Opt outputs are not fed into ThreeME. We showed that this reduction in energy demand drivers led to a 5.5% reduction in GDP. This outcome is particularly relevant to CGE modelers as they often oversimplify the energy system and its impact on the economy. Therefore, soft-linking can improve the CGEM results by accounting for ESM feedbacks that emerge from analyzing climate policies with rich bottom-up details.

Furthermore, we demonstrated that in this case study, the energy prices parameter is the primary feedback among four feedback parameters: productivity factors, energy mix, energy prices, and energy trade. The energy prices parameter reduces the energy activity drivers in 2050 by 15% on average compared to the NF stage. We illustrated that the energy prices of IESA-Opt increase the production cost of ThreeME commodities and consequently reduce the international competitiveness of domestic products. Therefore, high energy prices (resulting from IESA-Opt) decrease the exports, and thus, GDP and energy demand drivers. This outcome elevates the significance of international trade assumptions or the need for a global economy model while modeling a national energy-economy linked system.

In addition, as explained in the discussion section, the proposed soft-linking method and analyses can be improved in several ways, such as performing sensitivity analyses on primary scenario parameters (e.g., elasticities), using a global CGEM or an international scenario framework, increasing the sectoral detail of ThreeME, improving the price linking between models, providing in-depth economic analyses, and analyze the results considering high fossil fuel price projections.

Although there exist other studies that provide a transparent soft-linking methods for national models, the present study improves the literature by increasing the transparency level and quantifying the relevance of the feedback parameters in the utilized approach. Each soft-linking effort requires making particular assumptions depending on the underlying methodology and resolution of the used models. Therefore, comparing the results of soft-linking approaches would be challenging. However, readers can benefit from the higher transparency and diversity of approaches, and employ a mixed approach that is best suited for their study.

8.2. Research outcomes

The present research aims to provide insights into the linkages and interactions of future integrated energy systems with increasing shares of intermittent renewables in the electricity supply. More specifically, the main objective is:

"Providing quantitative insights into energy transition pathways using a framework approach which links bottom-up and top-down energy and economy models, covers the whole demand, supply, infrastructure and trade of energy, has a low entry-barrier, and features advanced capabilities, such as, wide range of flexibility options and hourly temporal resolution, tailored to answer future policy questions."

To address this objective, we framed three research questions that are answered in the following:

RQ 1: To what extent can we improve the methodology, technological and temporal resolution, and capabilities of national energy system models to address future policy questions?

As a first step, we reviewed the latest energy system modeling field improvements to identify best practices. We showed that it is not a practical conclusion to decide on the best model that addresses low-carbon energy systems challenges, as each model has specific pros and cons. Furthermore, due to the strong interconnection between energy and economy, mixed policy questions arise that require analyzing the technical, microeconomic, and macroeconomic aspects of the energy-economy system. Such analysis can be conducted by combining different models (i.e., soft-linking, hard-linking, or integrating). Therefore, we proposed two conceptual modeling suites, based on both optimization and simulation methodologies, in which the integrated ESM is hard-linked with both a regional model and an energy market model and soft-linked with a macroeconomic model. The choice of models, connection points, and scenarios depends on the energy system modeling aims, available expertise and resources, and access to models and datasets.

Then, we started developing the IESA modeling suite by formulating the core optimization model, IESA-Opt. IESA-Opt was designed as an LP formulation that minimizes the cost of investments, retrofitting, decommissioning, and operation of the energy system through the transition period. The optimization problem was subject to a set of constraints used to describe the feasible transition and operation ranges of all the technologies. We separated the constraints into three main categories based on their temporal resolution: yearly, daily, and hourly. Conventionally, models with a broad technological representation of energy systems could hardly adopt hourly resolutions to study the energy transition towards low-carbon technologies due to the extended problem size. This compromised the model's ability to address the challenges of variable renewable energy sources and the cost-effectiveness of cross-sectoral flexibility options. The IESA-Opt methodology presented a linear program model formulation that simultaneously adopted different temporal representations for different parts of the problem to overcome this issue. For instance, all electricity activities and their infrastructure representation followed hourly constraints to replicate system feasibility better. The operation of gaseous networks was settled out with daily constraints. Balancing the other activities of the system was represented with yearly constraints. Furthermore, the methodology adopted an hourly formulation to represent in detail six cross-sectoral flexibility archetypes: heat and power cogeneration, demand shedding, demand response, storage, smart charging, and electric vehicles. The model could use the available computational capacity thanks to the novel formulation.

Moreover, we focused on improving energy system flexibility options by describing them with an hourly temporal resolution. Flexibility options were modeled in three archetypes: combined heat and power (CHP), demand shedding, and conservational flexibility (i.e., load shifting, storage, passive storage, smart charging, and vehicle-to-grid). We demonstrated the primary role of flexibility options across different energy sectors in transitioning to a high VRES energy system. Further, compared to other ESMs, we demonstrated the role of seasonal energy storage options using the hourly time-steps approach instead of the time-slice method.

Also, we expanded the post-processing of the IESA-Opt model to provide an extensive list of parameters in detail. For instance, energy system costs were reported for all sectors, technologies, and periods, enabling users to identify the source of variations in the objective function quickly.

Furthermore, we quantified some modeling trade-offs by measuring the cost of increasing resolution in each modeling capability in terms of computational time and energy system modeling indicators, notably system costs, emission prices, electricity generation, and import and export levels. We showed that the memory requirements and problem size grow linearly with higher granularities in the transitional scope, similarly with the computational times. Moreover, the three flexibility enhancements with the most computational requirements were identified as shedding, vehicle-to-grid, and smart charging. At the same time, storage and demand response had the lowest impact on computational times. Furthermore, the representation of gas and electricity infrastructure imposed the highest burden on the solution, while hydrogen and district heating infrastructure affected the problem size and solution time the least.

Additionally, we investigated the role of software improvements and hardware specification on the methodology developments. Although we used commercial solvers (with free academic license), we adjusted their default settings to formulate tailor-made parameters that increased considerably the solving capacity and speed. In this regard, we used parallel solving methods to maximize available computational capacity. However, even by realizing software improvement potential, there is a need for huge computational capacity to solve such large-scale and high-detailed optimization problems. As a result, the level of methodological detail we could add was constrained by the available hardware. With the current high rate of computational hardware improvements, we will be able to include more details in models in the coming years. In the four years course of this study, we witnessed the hardware improvements and utilized state-of-the-art computational process units to expand IESA-Opt's level of details.

Finally, we expanded the IESA framework one step further by soft-linking the core IESA-Opt energy system module with a national macroeconomic model. Although there is ample literature on energy and economic model linking, they hardly describe the details and underlying assumptions regarding the linking process. For this purpose, we tailored the recently developed open-source ThreeME model to the IESA framework by aligning its sectoral definition with the IESA-Opt energy system model. Moreover, we presented a generic step-by-step methodology for soft-linking national energy systems and computable general equilibrium models. Furthermore, we implemented this methodology on two open-source models to demonstrate its impact on modeling results.

RQ2: What are the implications of model improvements on required data at specific resolutions and how data availability restrains such improvements?

The higher modeling capabilities and resolution entail a higher level of data requirements. Although with each improvement to the IESA modeling suite, we gathered, organized, and implemented the required data from open-access databases, we identified a need for higher data requirements.

For instance, IESA-Opt requires multi-year techno-economic data of more than 700 technologies in all sectors for both energy transformations (i.e., electricity, refineries, heat, hydrogen, gas, and biomass) and final demand (i.e., residential, services, agriculture, transport, and industry). This techno-economic data includes the overnight capital costs (OCC), fixed and variable operational and maintenance costs (FOM and VOM), technical lifetime, operation profile, capacity factor, and the input and output of energy, emission, and commodities.

Moreover, in this rich technological representation, cross-sectoral technologies are included, such as P2Heat, P2Gas, P2Hydrogen, P2Liquids, P2Mobility, and V2Grid, as well as the corresponding descriptions of their flexible hourly operation. These sectoral coupling technologies require further data on their flexibility requirements, such as, charging time for batteries, charging and discharging rate of thermal storage, available capacity of vehicles for participating in V2G, and shifting range of demand response technologies. The cross-sectoral flexibility is a key capability of IESA-Opt, but it requires a significant amount of data gathering and technology description effort to be able to provide even more insightful analyses. The current flexibility descriptions in the model are focused on few technologies; therefore, there is a need to expand the list of technologies that can provide flexibility to the energy system. We expect this expansion to lower the transition costs and reshape the cost-optimal system configuration.

Furthermore, exogenous technological learning, efficiency improvements, and decommissioning and retrofitting parameters are also included in the formulation. Thus, these parameters need to be estimated in the reference scenario or be implemented according to a specific policy.

Additionally, the energy policies of neighboring countries, particularly regarding power generation and trade, should be taken into consideration in order to effectively model the energy trade. This includes the power generation capacity projections, expected interconnection capacities between countries, hydro storage capacity, and hourly profile of solar and wind availability in each node.

In addition to GHG emissions related to the energy system (divided into emissions within and outside the Emissions Trading Scheme (ETS)), the model also considers the emissions from non-energy sources, such as enteric fermentation, fertilizers, manure management, and refrigeration fluids. Although energy related emissions are calculated endogenously in the model, non-energy related emissions require exogenous Marginal Abatement Cost (MAC) curves.

Further, there is a need for techno-economic data of electricity lines, gas (i.e., natural gas, hydrogen, CCS), and heat pipelines including investment costs and losses per km, capital cost and losses of transformer and compressor units, operational costs, maximum available capacity, lifetime, and buffer capacity (for gaseous networks). We found that representing infrastructure in the model requires a complex data collection process, as many costs and operational parameters are spatially sensitive (e.g., a gas pipeline in a mountain range is more expensive than a plain). IESA-Opt still has enormous scope for improvement in this regard. Better data availability could enable the representation of intriguing transitional options, such as industrial clusters for heat recirculation or district heating purposes or even for H_2 or CO_2 consumers.

Although the data for well-described technologies were usually available, it was challenging to find or assume the required data of some novel technology options, such as the demand response in the residential sector. Therefore, due to lack of data, we did not disaggregate further this technology into, for example, demand response for built environment heaters and rest of appliances. For such technologies, there is a need for either “close enough” assumptions (e.g., from other models or studies) or sensitivity analyses.

Moreover, some technologies had a wide range of techno-economic data that could significantly affect the scenario results. For instance, to investigate the role of nuclear power in the Dutch energy transition, we identified the major uncertain parameters: capital cost, interest rate, VRES deployment potential, the flexibility of SMRs, and cross-border electricity volume and price. For such uncertain parameters, we first identified a range, and, then, conducted a set of sensitivity analyses by varying the parameter values within the range. Using this approach, we showed how the economic feasibility of national nuclear power investments could vary depending on the value of the above parameters.

In addition, we experienced new data requirements by adding a macroeconomic model to the IESA framework. Computable General Equilibrium (CGE) models highly depend on the base year’s elasticity values and social accounting matrix. The elasticities determine the substitution rate between production factors, trade, and intermediary commodity consumption. Therefore, the variation in economic behavior can lead to variations in elasticities, which can highly affect the results. In the present study, we merely used default elasticities based on historic economic behavior. However, due to changes in economic policies, these elasticities can vary considerably during the energy transition course. For instance, we showed that trade elasticity plays a crucial role in determining the competitiveness of domestic products and, thus, economic growth. Moreover, we realized that the choice of the base year, which determines the starting point of the CGE model, can impact the projected economic growth. For instance, choosing 2021 as the base year might underestimate the economic growth as it was under the temporary impact of the covid-19 pandemic. On the other hand, the chosen base year should not be too far from the present to represent the most current state of the economy and energy system. Furthermore, we demonstrated the need for data on international trade policies as they highly affect national economic growth. In the present study, we assumed a fixed energy trade and linear price increase of other commodities. However, this assumption is far from reality as the international price of commodities can change considerably based on different national policies, notably climate policies.

In summary, we identified several critical data requirements that affect the modeling results:

1- Techno-economic data of current and future technologies (i.e., current low TRL technologies) per region. This includes the projection of technological costs and learning, energy balance of each technology, efficiency improvements, and operational constraints. While analyzing the role of flexibility options, we would particularly need flexible operational constraints of such technologies (e.g., battery charging rate, heat storage losses, electrolysers' shedding capacity).
2- Investment and primary energy potential per region that contains fossil fuel extraction or import availability and costs, available land or roof for wind or PV installations onshore and offshore, available underground capacity for energy or emission storage (heat, hydrogen, natural gas, or CCS).
3- Activity demand projections per region that determine final demand of the energy system. By using the soft-linking method, this input data can be converted from a general equilibrium model.
4- Recent representative macroeconomic data per region that comprises the latest social accounting matrix and elasticities. Moreover, the projection of elasticities is required to account for policy-based economic changes.

RQ3: How can higher modeling capabilities and resolutions inform Dutch energy transition scenarios with respect to environmental policies, direction and timing of investments, and its impact on the economy?

We were able to effectively demonstrate the changes in the Dutch energy transition scenarios thanks to the high technological and temporal resolution of the IESA-Opt model. We showed that even in a high decarbonization scenario, fossil fuels would play a significant role as many causal factors, such as scope two and three emissions, international transport, exports of refined products, and industrial feedstock, were not included in the latest available climate policies of the Netherlands.

Moreover, we demonstrated that to displace oil-based products from the energy mix, a policy package comprising scope two and three emissions, international transport, feedstock for high-value chemicals, and refined oil products exports would be required on top of the current emission reduction targets. However, to make this transition affordable and effective, it would be necessary to ensure the availability of biomass resources (around 530 PJ/year) together with the development of carbon capture utilization and storage (CCUS) technologies (i.e., BECCS). Biomass plays a crucial role in the final years when it is being supplied to produce olefins to produce industrial feedstock in the chemical sector, which, next to biofuels and other biomass sources, account for over 500 PJ, that is, approximately a quarter of the share of renewables. This role of biomass is largely due to the possibility of importing biofuels (330 PJ) and wood (320 PJ), the values of which are assumed to be intermediate values provided by the two TNO scenarios for a climate neutral energy system for the Netherlands (i.e., ADAPT and TRANSFORM [166]).

We showed that the Dutch energy demand in 2050 presents a significant reliance on renewable energy sources, such as wind (800 PJ) and solar (300 PJ). However, oil (880 PJ) and gas (1050 PJ) constitute almost half of the final energy demand as they are required for heat applications, industrial feedstock, refined oil products for export, and international transport fuel.

Additionally, we showed that the ETS sectors undertake the greatest abatement responsibility as they present a pronounced and accelerated reduction path, while even realizing negative emissions in 2050. To reach 2050 climate target, the emission price increases to almost 560 €/ton of CO_2. This is almost four times higher than the 2030 price, which indicates that, if the targets are adhered to seriously, the transformation required for the decade after 2040 will impact the system more aggressively than the impact we are experiencing in this decade.

Moreover, the costs of the Dutch energy system will be up by 60% in 2050 compared to 2020, with the residential and services sectors contributing the most with a 75% rise in costs. This is mainly due to the implementation of better insulation, resulting in a higher capital cost, but a decrease in fuel costs. In contrast, the agricultural sector sees a 22% drop in prices from 2020 due to an increase in capital and lower fuel expenses, while the transport sector will have a steadily growing capital intensity until 2035 and then a 15% higher cost than in 2020. Further, the industry sector will have a 66% cost increase from 2020, mainly caused by high fuel costs. Lastly, the power generation sector costs increase considerably by 150%, which is mainly due to vast investments in VRES.

We also showed the temporal dynamics of gaseous networks during the energy transition. The natural gas load would keep its seasonal trend in 2050 with peaks of 60% in some winter days, compared to the summer load. For hydrogen and CCS pipelines, we see an inverted trend, where load is higher in the summer thanks to the availability of cheaper electricity. Lower electricity prices promote the use of electrolysers in the summer, which consequently triggers an increased use of CO_2 from the CCUS network to produce synthetic fuels.

Thanks to high technological resolution of IESA-Opt and its multi-year optimization, we were able to demonstrate technological changes in each Dutch sector. For instance, to reduce emissions by electrification, the industrial sector starts adopting novel technologies such as electrolytic steel production (40% of steel production) or solid-state ammonia synthesis (SSAS) for producing 50% of ammonia. In addition, electrolysers are being adopted at both decentralized and centralized locations to produce around 80 PJ of hydrogen, which is mainly used for refineries. In addition to electrification, other decarbonization pathways can be observed in the industry sector, such as the use of biomass to produce olefins and the adoption of heat from biomass with CCUS to provide negative emissions. As a general observation, CCUS is widely adopted in the industrial sector owing to its high CO_2 storage capacity and the possibility of using it as a sink (e.g. the production of synthetic fuels from electricity and CO_2 in 2050). The transport sector undergoes a complete transformation. The model run of the reference scenario results in the predominant presence of electric vehicles (EVs) as the cost-optimal configuration for the road subsector. Similarly, within the navigation subsector, heavy oil ships were substituted with compressed-natural-gas-engine (CNG-engine) ships. The rest of the transport sector remains largely unchanged, primarily because trains are already electric and because emissions from kerosene planes are not addressed by the existing climate policy. For the residential and services sectors, the model determines the optimal path for retrofitting all the spaces to the maximum level of insulation as quickly as possible. It then uses boilers, district heating, and electric heat pumps to meet the reduced residential heat needs and gas CHPs and hybrid heat pumps to supply heat for service spaces. A system running on geothermal energy and hot water storage tanks is adopted by the scarcely used district heating network to provide flexibility to the heat supply (that is coupled with the power system). The agriculture sector uses geothermal energy to satisfy its heat demand. However, this outcome would be different if spatially sensitive data were used to only allow certain regions to adopt geothermal energy according to its availability.

In addition, we demonstrated the implications of high electrification (i.e., triple load from 2020 to 2050) on the Dutch energy system. The high electrification was simultaneously driven by an increase in the external trading flows as well as by a profound electrification of both the final and energy sectors. It was observed that the Netherlands evolved from a net importer to a net exporter of electricity, with an increase in volume facilitated by the resulting interconnection capacity expansions. The high electricity load in 2050 was triggered by the adoption of electrified industrial technologies, (moderate) electrolyser use, deployment of the electric transport fleet, and choice of electric technologies for heating. Finally, it is worth highlighting that the maximum level of system curtailment was less than 50 PJ, which accounted for less than 5% of the electricity produced by VRES in 2050. Such efficient use of VRES electricity was fundamentally enabled because of the crucial role of cross-sectoral flexibility.

We demonstrated the inevitable role of biomass and CCS in reaching Dutch emissions reduction targets using sensitivity analyses. In the presence of high biomass (770 PJ) and CCS (50 Mton CO_2) availability, the system costs increase only by 4% in 2050, compared to the 'no emission target' scenario. By limiting their potential, either reducing CCS capacity to 25 Mton (and keeping biomass at 770 PJ) or reducing biomass availability to 60 PJ (and keeping 50 Mton CCS), the system costs increase from 4% to 6%. However, the system costs increase significantly to 24% in 2050 compared to the 'no emission target' scenario, if both biomass and CCS are limited (60 PJ and 25 Mton, respectively).

Although international navigation and aviation were not considered in the Dutch climate policy package at the time of this study, we investigated the impact of decarbonizing these sectors on the national energy transition. Considering that the Netherlands wants to keep its current high Oil-Based Products (OBPs) export levels and has high availability of biomass (1250 PJ) and biofuels (750 PJ), we showed that imposing 95% emissions reduction target on the international transport sector increases system costs by 30%, which is considerable.

Since IESA-Opt model is a partial equilibrium model, it requires exogenous demand drivers that are determined by expected economic activity. An increase or decrease in economic activity in specific sectors, can cause the energy transition to become considerably more expensive or cheaper, respectively. We showed that for the Dutch energy transition, this impact is not considerable. For instance, by decreasing the activity demand of the transport or industry sectors by 10%, system costs decrease by less than 2%.

Further, we concluded that nuclear power could play a complementary role (in parallel to wind and solar power) in supporting the Dutch energy transition from the sole techno-economic point of view. We demonstrated and analyzed the impacts of having a clear baseload energy source (i.e., nuclear power) in transitioning to a net-zero Dutch energy system with high shares of VRES. It was shown that the LCOE alone should not be used to demonstrate the economic feasibility of a power generation technology. For instance, under the default techno-economic assumptions, it is cost-optimal for the Netherlands to invest in 9.6 GWe nuclear capacity by 2050, although its LCOE is 34 €/MWh higher than offshore wind. Further, we found that nuclear power investments can reduce demand for variable renewable energy sources in the short term and provide higher energy independence (i.e., lower imports of natural gas, biomass, and electricity) in the long term. Moreover, we demonstrated that the economic feasibility of Dutch nuclear power investments could vary considerably depending on the cross-border electricity trade assumptions. Nuclear investments follow three primary behaviors depending on the cross-border electricity price and available trade volume. First, with low trade volumes, the model invests in nuclear power to avoid the high costs of flexibility supply options. Second, with high trade volumes and import prices, the model invests in nuclear to avoid high import costs. Third, with high trade volumes and low import prices, the model substitutes nuclear power with cross-border trade volumes. In addition, with a 3% interest rate value (e.g., EU taxonomy support), even high-cost nuclear (10 B€/GW) can be cost-effective in the Netherlands.

Furthermore, we described a step-by-step soft-linking process and its underlying assumptions applied to the Netherlands as a case study. Our analyses showed that by considering the impacts of emission reduction targets (e.g., net-zero by 2050), the projected Dutch GDP reduces by 5.5% in 2050 compared to the baseline economic scenario. Furthermore, we illustrated that this GDP reduction is primarily because of the high energy prices of IESA-Opt that increase the production cost of commodities in ThreeME and consequently reduce the international competitiveness of Dutch domestic products. For instance, for the steel production sector in 2030, IESA-Opt decommissions the current blast furnace technology and instead invests in the direct reduction from hydrogen technology. While blast furnace technology mainly requires coal, the latter primarily relies on hydrogen and electricity. Moreover, as the output of IESA-Opt, the price of electricity and hydrogen should increase considerably in 2030 to reach the 55% GHG emission reduction policy. As a result, the weighted average energy price for steel production increases by 270% from 2020 (coal-based) to 2030 (hydrogen and electricity-based). This price upsurge increases the price of steel commodity by 44% from 2020 to 2030. In contrast, in the same period, the international price of steel increases merely by 22% (i.e., 2% growth per year), which results in the lower competitiveness of domestic steel compared to the international market. These outcomes elevate the significance of considering the whole economy while analyzing energy transition scenarios.

In conclusion, we found that there is no single technology or energy carrier that can carry the whole energy transition load. Therefore, a cost-effective and timely Dutch energy transition requires having all technological options (e.g., biomass, biofuels, CCS, BECCS, DAC, synthetic fuels, hydrogen, ammonia, wind, solar, nuclear, electrified transport and industry, and insulated built environment) on the table rather than investing heavily on specific options (such as hydrogen or wind power).

8.3. Recommendations

There are several directions which we would suggest focusing on in order to continue this research. We categorize our recommendations for the research community, policy-makers, and market-parties.

A - Research community

Robust optimization and uncertainty

In this study, we did not focus on uncertainty due to lack of time. However, we tried to increase the robustness of the results by performing several sensitivity analyses. The downside to this approach is that running energy system models takes a long time, and uncertainty analyses can add significantly to the computational burden. However, we developed the IESA-Opt framework by considering the need for addressing uncertainty. Therefore, the model is designed to be agile and be able to run in parallel. These capabilities help other researchers to conduct sensitivity analyses without the need for making major changes to the model's methodology. Besides, energy modelers can further reduce the run times by implementing novel methodologies. For example, electricity related processes can be modeled hourly, while gas and hydrogen networks can be balanced daily (as it was done in this study). Moreover, where possible we can reduce the complexity of the model by assuming a linear formulation as solving linear models is considerably faster than mixed-integer and non-linear models (e.g., by neglecting the unit commitment constraint).

Robust optimization is an optimization methodology which provides solutions that are not severely impacted by uncertainty in the input parameters. It allows for more flexible decision making by focusing on minimizing the worst-case performance rather than the expected performance. This technique is particularly useful in decision making with uncertain inputs in areas such as climate modeling, energy transition, and finance research.

Robustness in energy system modeling is an essential requirement for successful energy transition planning. The future potential, availability, and costs of technologies and energy carriers are uncertain; however, we need to identify no regret policies and investments that contribute to emission reduction goals in a cost-effective and timely manner. A prime example of this uncertainty that was analyzed in this study is investments costs of nuclear power, which can vary greatly from a project to project. Additionally, the energy transition is composed of a wide range of variables and actors with different needs and preferences, all of which come with their own unique levels of uncertainty. For this reason, it is important to ensure that results from energy system models are robust enough to account for the complex dynamics of the energy transition.

Data improvement

It is important to mention that, given the broad energy system definition of IESA-Opt, it is sensitive to the data quality fed into the model; hence, collecting, managing, and maintaining the database comprises a process of continuous improvement. This expands the scope for improvement and opens the door for other potential future research efforts. For instance, currently, the available data of the hourly demands of certain technologies are too generic (e.g., standard load, day and night, and flat profiles are applied to many technologies owing to the lack of available data) and could be improved, which could yield exciting studies on the evolution of demand profiles in the transition. Furthermore, the EV technologies and infrastructure catalog could be expanded to compare the cost-effectiveness of options.

For instance, during the study, we had to make some assumptions due to a lack of either data or the time required to gather the data. For instance, in chapter six, we assumed the same 5% discount rate for all technologies in the reference and nuclear scenarios to avoid any bias for VRES or nuclear. However, the sensitivity results showed that the value of the discount rate considerably affects the cost-effectiveness of nuclear investments. Therefore, for future studies, we suggest using technological-specific discount rates based on national or international policies (e.g., EU taxonomy). Further, we had to make assumptions regarding the cross-border electricity trade as the evolution of the European electricity market, particularly the Netherlands' neighboring countries, is highly uncertain. Such assumptions did not consider the energy transition policies of neighboring countries and their impact on the price and hourly availability of electricity for trade. Moreover, the model scenario analysis shows that wind energy plays a significant role in the 2050 Dutch energy mix. However, this analysis described the offshore wind as a single technology without considering different cost profiles based on spatial potentials that can affect both the Netherlands and the North Sea power dispatch considerably, as well as the costs of the energy transition. Also, we assumed perfect foresight for modeling the energy transition, and thus, no forecasting errors were included in the operation profile predictions. This is another source of extra transition costs when dealing with large amounts of VRES in the system. In addition, for this analysis, we only used one climate year for all the VRES availability profiles in the whole transition; thus, we neglected the impact of climate change on resource availability and the different operation settings that the system might confront. Furthermore, the technological description is not yet fully extended. Industrial activities should be further disaggregated to account for more decarbonization technologies and cross-sectoral synergies (e.g., mode-flexible processes such as smelters, paper mills, and local waste heat-recirculation networks).

In addition, due to lack of data (e.g., elasticities, more detailed social accounting matrix, and international trade policies) we had to make several assumptions regarding the macroeconomic modeling and its link with the energy system. For example, we assumed that the energy model's capital costs represent the sector's whole capital costs. However, this is not the case, as an energy-related capital cost of a specific sector only represents a share of its total investment costs. Moreover, in this study, we merely used default elasticities. However, there is room to investigate the role of variations in elasticities in the final results. For instance, as was shown in the results section, trade elasticity plays a crucial role in determining the competitiveness of domestic products and, thus, economic growth. Also, we had to choose 2015 as the base year for the ThreeME model since 2020 might underestimate the economic growth as it was under the temporary impact of the covid-19 pandemic. This choice was not in harmony with IESA-Opt as it was calibrated in 2020. Moreover, we assumed a steady-state increase in international energy and commodity prices in ThreeME. However, this assumption is far from reality as the international price of commodities can change considerably based on different (inter)national policies, notably climate policies.

Being able to collect, manage, and maintain the required data (e.g., techno-economics of technologies, resource potentials, land availability, efficiency and technological learning, operational profiles, social accounting matrix, and elasticities) with a high level of detail (e.g., hourly or daily variations per region) and disaggregation (e.g., energy and economy sub-sectors) is essential for effective energy system modeling. With availability of such ‘high-quality’ data, models can incorporate up-to-date information about the energy system and help to guide decisions about energy policies and investments. Improved data quality can also help to capture the complexity of the energy system and allow for more detailed analysis. Moreover, high-quality data is important for improving energy system modeling accuracy. Improved accuracy can lead to better decisions about investments in different energy technologies. It can also help to facilitate a better understanding of how different energy technologies interact with each other and the broader energy system. Better data quality and improved modeling accuracy are both essential for the successful transition to a more sustainable energy system.

Improving the soft-linking

The proposed soft-linking method and analyses can be improved in several ways, such as performing sensitivity analyses on primary scenario parameters (e.g., elasticities), using a global CGEM or an international scenario framework, increasing the sectoral detail of ThreeME, improving the price linking between models, providing in-depth economic analyses, and analyze the results considering high fossil fuel price projections.

Expansion of the model to other regions

The presented study focused on the national geographical scale. However, we showed how the cross-border energy trade could impact the cost-optimal national investments. Therefore, we suggest expanding the model to other regions, particularly the EU and Netherlands’ neighboring countries. This suggestion was partly made by another Ph.D. student, Rafael Martinez Gordon, who successfully expanded the IESA framework to the North Sea region, comprising five countries. However, the IESA framework can be expanded further to other EU countries, resulting in consistent energy system analyses where cross-border energy trade is optimized endogenously.

Further analyzing the economic results

The presented study merely analyzed the aggregated economic indicators such as the export and GDP levels. However, the relevance of soft-linking on more detailed economic indicators was not discussed. Therefore, there is a need for an in-depth analysis of the results that would require looking at additional economic indicators, decomposing economic impacts (in particular between substitution effects and income effects), and sensitivity analysis of critical parameters (e.g., elasticities) of the model. Since these in-depth economic analyses fall out of this study’s scope, we suggest further research.

Further scenario studies

In this study, we assumed a high import potential of critical low-carbon energy sources: biomass, bioethanol, biodiesel, biokerosene, and hydrogen. However, their import potential and price significantly depend on global and regional energy market developments in the coming decades. Moreover, we assumed business-as-usual fossil fuel prices. In contrast, the natural gas and oil prices increased considerably in 2022 due to the disrupted supply side, particularly the Russian natural gas supply to Europe. Therefore, we highly suggest further investigating more scenarios with the IESA suite, in particular, the impact of changes in price and availability of energy carriers on the national energy transition path.

B - Policy-makers

To meet the goals of the Climate Act and transition to a climate-neutral energy system by 2050, many decisions and changes must be made. This transition requires advanced knowledge and up-to-date information on the development and implementation of energy technologies, their impacts on the environment and use of space, and other social, economic, and political considerations. To successfully realize this transition, integrated knowledge in a framework format must be accessible to those making policy and decisions regarding the energy transition.

Having a comprehensive understanding of energy is essential in order to effectively discuss and evaluate its connections and implications. Too often, conversations and policy-making focus on individual energy sources (such as solar, wind, biomass, or nuclear energy) or energy carriers (electricity, hydrogen, fuels) without considering the interconnectedness between them. It was shown in our studies that each technology or energy carrier plays a role in the Dutch energy transition. Not only diversifying the support in several clean energy carriers reduces system costs, but also it decreases the risk of dependency on a specific technology. For instance, we showed that investments in nuclear power reduces energy transition costs while providing stability to the power system and reducing dependency on huge investments in wind and solar capacity.

Furthermore, the connections between the subsurface (e.g., CAES, thermal energy storage, geothermal potential, and CCS capacity) and the land availability (e.g., offshore and onshore wind turbines, solar PV, nuclear power plant, agriculture and horticulture, biomass, and infrastructure) need to be considered for a successful energy transition. For instance, in order to create a sustainable energy system, extra space is needed for the production, conversion and transport of energy. It is necessary to consider how much space is needed, where it should be located and if it is possible to have multiple uses of space. Furthermore, it is important to find a way to make good decisions regarding the various interests. Taking the amount of space already present into account. Additionally, there must be collaboration between different sectors (built environment, agriculture, industry, mobility) to achieve an optimal solution. Lastly, a successful energy transition requires a global perspective and not just one that is limited to regions or municipalities. For example, we demonstrated the critical role of cross-border electricity trade in long-term energy system planning. We recommended policy makers to establish long-term electricity trade alliances with EU countries, in particular, neighboring countries. Such a well-functioning electricity market can play a major role in providing flexibility to the power system while providing reliable and affordable electricity.

Moreover, we must also be aware of the danger of viewing the energy transition too much as an engineering issue, while the attitudes and actions of people and businesses, regional and national decision-making processes, are just as vital. Sustainable options must be practical, accessible, and inexpensive for all purposes. Only then can a comprehensive energy transition come to fruition, one that is widely accepted in society.

Furthermore, the materials and energy transitions are interconnected and must be seen in tandem in order to achieve sustainability. The materials transition looks to make efficient use of available materials, and the circular economy is an effective tool for this. As such, the materials transition impacts the energy transition by determining the availability and cost of materials used for clean energy technologies, such as solar cells, batteries, and wind turbines, as well as the emissions that affect air quality. To make a successful transition to sustainability, these transitions must be considered together.

Therefore, there is a need to improve current models and databases in a framework format where the different aspects of energy transition are interlinked:

- Linking the energy transition to economic and social developments (e.g., the impact of the energy transition on the housing market, sector structure and employment, international competitive position, the energy poverty problem, distribution of end-user costs at district level).
- Linking the energy transition with the transition to sustainable and smart mobility and logistics and changes in the spatial distribution of living and working (e.g., the implications of modal shift, electric charging, digitalization and platform services, and the development of aviation and shipping on energy use and energy infrastructure).
- Linking the energy transition with the economy (e.g., greening the financial markets by breaking down existing barriers to this, so that green investments by companies and citizens can be better financed).
- Linking the energy transition to the environment (e.g., land use, land use change, and forestry, land availability for renewable energy production or agriculture products, food supply emissions, emissions that cannot be eliminated completely)
- Linking the energy transition to the materials and resources (e.g., rare earth material demand, mining and availability of materials, material recycling)

On one hand, equipping policymakers and decision-makers in the energy transition with the latest knowledge and data, as well as in-depth analyses of the repercussions of the transition, can encourage wiser decisions and more balanced decision-making, thus ensuring that the costs of the energy transition are kept reasonable, and the benefits are maximized. On the other hand, policy actions should also be coordinated as they are interlinked (like the modeling framework). We showed the insights that such a framework can provide by linking different models at different scales. However, gaining an understanding of how the impacts of an energy transition policy can feed back and shape other policy areas and the scenarios that can result is essential. For instance, spatial planning is an integral part of determining the potential for sustainable energy use, while environmental demands can have a significant effect on the scale of energy technology deployment and associated cost levels. Therefore, policy-makers can bring higher harmonization across different policies, by taking advantage of such modeling frameworks that help to facilitate the implementation of the energy transition in a timely manner; for instance, by identifying the various impacts at an early stage, by finding optimal(er) pathways, and by minimizing the costs of implementation.

C - Market-parties

The Integrated Energy System Analysis (IESA) framework is a powerful tool that helps market-parties identify long-term trends and potential investments in energy transition, as well as provides insight into the timing of investments and potential risks associated with them. The IESA framework offers a system-wide perspective that considers the interactions between different energy sectors and can be used to develop business models that are tailored to the energy transition. This helps market-parties make informed decisions about when and where to invest, giving them a competitive edge. As an example, we highlight the following points:

Invest in flexibility options

The ability to invest in flexible processes has become an increasingly important factor in managing the highly electrified energy system of today. This is particularly useful in the face of increasing share of VRES, which can cause fluctuations in the energy system that can be difficult to manage. The key to a successful energy system is the ability to respond to these fluctuations and to be able to take advantage of arbitrage opportunities that can arise. This can be achieved through investments in flexible processes such as electrolysers, batteries, and flexible industrial processes (e.g., Solid-State Ammonia Synthesis).

In our research, we were able to show the high value of flexibility options in stabilizing the highly electrified energy system. We recommend that market-players invest in these flexible processes in order to maximize their potential profits from arbitrage opportunities through energy cost reduction and both the intra-day and day-ahead electricity markets. Not only can these investments help to better manage the energy system, but the profits generated from the arbitrage opportunities will result in major returns for the investors.

Carbon capture technologies

The need for carbon capture processes to offset both embedded carbon in end-use products and non-energy emissions is becoming more pressing as scope three emissions are being included in climate policies. Carbon capture and utilization (CCU) processes such as BECCS and Direct Air Capture (DAC) offer viable solutions to reducing these emissions and reaching the net-zero target by 2050.

However, our research shows that reaching this target by 2050 would require steep increases in the cost of carbon dioxide. The carbon dioxide prices could reach ten times of 2020 values, making the business case of carbon capture processes such as BECCS and DAC significantly more profitable. Such increases in the carbon price would allow for incentive-based policies to encourage the development of CCU processes and, thus, reducing emissions.

At the same time, it is important to ensure that these CCU processes are economically and technologically feasible. With the increase in carbon dioxide prices driving higher incentives for carbon capture and utilization processes, it is essential that their feasibility and efficiency are assessed by the private sector in order to ensure their successful implementation at the right time. Unlike the other example (i.e., investments in flexibility options) that is a hot topic nowadays, the need for carbon capture technologies will become prominent in the next decade. Market-parties who have done R&D and are prepared, can harvest the coming investment opportunities on-time.

Appendix A Consideration of non-energy related emissions in IESA-Opt

To cover all the GHG emissions forms considered within the decarbonisation reduction targets, data from the 2017 national GHG emission inventory report were used [56]. This helped identify which emissions were not yet covered by the model and prioritise which emission sources should be included to increase robustness in the emission reduction analysis. A summary of the sources, emission activity, emission form, evolution from 1990 to 2017, and how the model deals with each is presented in Table 64.

Source	Activity detailed	Form	Units	1990	2016	2017	Modelled
Energy-related	Fuel Combustion	CO2	MtonCO2eq	154.5	158.6	156.2	Explicitly
Agriculture	Enteric fermentation	CH4	MtonCO2eq	9.2	8.8	8.7	MACC
Agriculture	Manure management	CH4	MtonCO2eq	5.4	3.9	3.9	MACC
Industrial Production	Ammonia production	CO2	MtonCO2eq	3.7	3.8	3.9	Explicitly
Waste	Managed waste disposal on land	CH4	MtonCO2eq	13.7	2.8	2.6	Aggregated
Energy-related	Fuel Combustion	CH4	MtonCO2eq	0.9	1.6	1.7	Explicitly
Agriculture	Inorganic fertilisers	N2O	MtonCO2eq	2.5	1.5	1.6	MACC
Industrial Production	Refrigeration	HFC	MtonCO2eq	0	1.5	1.5	MACC
Agriculture	Organic N fertilisers	N2O	MtonCO2eq	0.8	1.3	1.4	MACC
Energy-related	Fugitive Emissions	CO2	MtonCO2eq	0.9	1.1	1.1	Excluded
Agriculture	Urine and dung from grazing animals	N2O	MtonCO2eq	3	0.9	0.9	Aggregated
Agriculture	Manure management	N2O	MtonCO2eq	0.9	0.8	0.8	MACC
Industrial Production	Caprolactam production	N2O	MtonCO2eq	0.7	0.8	0.8	Explicitly
Industrial Production	Other mineral use	CO2	MtonCO2eq	0.48	0.77	0.79	Aggregated
Agriculture	Cultivation of organic soils	N2O	MtonCO2eq	0.9	0.7	0.7	Aggregated
Industrial Production	Other chemical industry	CO2	MtonCO2eq	0.6	0.5	0.7	Explicitly
Agriculture	Indirect N2O Emissions from managed soils	N2O	MtonCO2eq	1.6	0.6	0.6	Aggregated
Energy-related	Fuel Combustion	N2O	MtonCO2eq	0.3	0.6	0.6	Explicitly
Energy-related	Fugitive Emissions	CH4	MtonCO2eq	1.9	0.6	0.5	Excluded
Industrial Production	Petrochemical and carbon black production	CO2	MtonCO2eq	0.3	0.5	0.5	Explicitly
Industrial Production	Indirect CO2 emissions	CO2	MtonCO2eq	0.9	0.5	0.5	Aggregated
Agriculture	Crop residues	N2O	MtonCO2eq	0.5	0.3	0.3	Aggregated
Industrial Production	Cement production	CO2	MtonCO2eq	0.42	0.24	0.3	Aggregated

Source	Activity detailed	Form	Units	1990	2016	2017	Modelled
Industrial Production	Nitric Acid production	N2O	MtonCO2eq	6.1	0.3	0.3	Aggregated
Industrial Production	Petrochemical and carbon black production	CH4	MtonCO2eq	0.3	0.3	0.3	Explicitly
Industrial Production	Lime production	CO2	MtonCO2eq	0.16	0.17	0.23	Aggregated
Industrial Production	Paraffin wax use	CO2	MtonCO2eq	0.1	0.2	0.2	Aggregated
Industrial Production	Other ODS Substitute	HFC	MtonCO2eq	0	0.2	0.2	Aggregated
Waste	Wastewater treatment and discharge	CH4	MtonCO2eq	0.3	0.2	0.2	Excluded
Industrial Production	Ceramics	CO2	MtonCO2eq	0.14	0.12	0.12	Aggregated
Industrial Production	Other Soda Ash uses	CO2	MtonCO2eq	0.07	0.12	0.12	Aggregated
Industrial Production	Fluorochemical production	HFC	MtonCO2eq	6.4	0.2	0.1	Aggregated
Industrial Production	Lubricant use	CO2	MtonCO2eq	0.1	0.1	0.1	Aggregated
Industrial Production	SF6 and PFC from other products use	SF6	MtonCO2eq	0.3	0.1	0.1	Aggregated
Industrial Production	N2O from product uses	N2O	MtonCO2eq	0.2	0.1	0.1	Aggregated
Waste	Biological treatment of solid waste	CH4	MtonCO2eq	0	0.1	0.1	Excluded
Waste	Biological treatment of solid waste	N2O	MtonCO2eq	0	0.1	0.1	Excluded
Waste	Wastewater treatment and discharge	N2O	MtonCO2eq	0.2	0.1	0.1	Excluded
Industrial Production	Glass production	CO2	MtonCO2eq	0.14	0.1	0.008	Aggregated
Agriculture	Liming	CO2	MtonCO2eq	0.2	0	0	Excluded
Industrial Production	Fluorochemical production	PFC	MtonCO2eq	0	0	0	Excluded
Industrial Production	Iron and steel production	CO2	MtonCO2eq	0.05	0	0	Excluded
Industrial Production	Aluminium production	CO2	MtonCO2eq	0.45	0.1	0	Excluded
Industrial Production	Aluminium production	PFC	MtonCO2eq	2.6	0	0	Excluded
Industrial Production	Other non-specified	CO2	MtonCO2eq	0	0	0	Excluded
Industrial Production	Semiconductors	PFC	MtonCO2eq	0	0.1	0	Excluded
Industrial Production	Other process emissions	CO2	MtonCO2eq	0.1	0	0	Excluded
Total				**222**	**195**	**193**	

Table 64, Summary of the inventory of emission sources and forms in the Netherlands. LULUCF.

Based on the inventory shown in the above table, the following approach included the emission sources in IESA-Opt. First, from all the emissions that were not yet explicitly accounted for by the activities in IESA-Opt as fuels or industrial processes (which accounted for 85% of the total emissions in 2017), the most significant ones were extracted—being the latter: enteric fermentation (CH4), manure management (CH_4 and N_2O), organic and inorganic fertilisers (N_2O), and refrigeration (HFC). Another reason for selecting these sources is that reliable data were found to incorporate their MACC curves into the model accordingly with the IMAGE model database [22,57].

Based on the above data, the following activities were defined to include all non energy-related emissions in IESA-Opt:

1. CH_4 emissions from enteric fermentation.
2. CH_4 emissions from manure management.
3. CH_4 emissions from other sources (aggregated).
4. N_2O emissions from manure management.
5. N_2O emissions from fertiliser utilisation.
6. N_2O emissions from other sources (aggregated).
7. F-gas emissions from the use of HFC as a refrigeration fluid.
8. F-gas emissions from other sources (aggregated).
9. CO_2 emissions from other sources (aggregated).

The resulting MACC curves used in IESA-Opt for the nine abovementioned sources of non energy-related GHG emissions are reported in Figure 81.

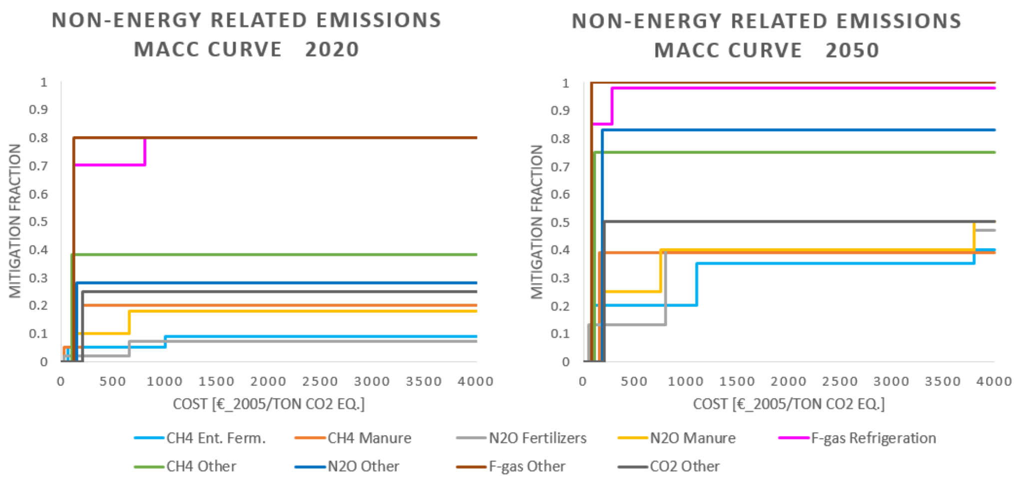

Figure 81, MACC curves of non-energy-related GHG emissions for 2020 and 2050 as considered in IESA-Opt[51].

[51] Note: MACC costs reported in the figure are expressed in €_2005 as those were the units used by the data source, but input data in IESA-Opt is expressed in €_2019.

Appendix B EU Power system representation in IESA-Opt

The representation of the EU power system is mainly extracted from COMPETES model [27] in terms of nodal representation and technologies considered, as well as the parameters used for IESA-Opt. In terms of the nodal representation, only one modification was made to COMPETE's representation, and this was to join both eastern and western Denmark nodes into one single node. The complete nodal representation is shown in Figure 82.

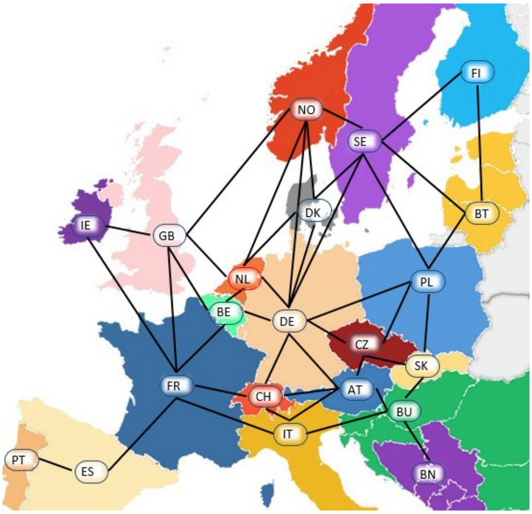

Figure 82, Nodal representation of the European power system considered in IESA-Opt.

The operational parameters of the generation technologies required by the model consist of both economical and operational components. The list of technologies, and operational parameters assumed for the European power system are shown in Table 65[52].

Table 65, Assumed parameters of the power generation technologies

Technology	Investment 2020	Investment 2050	FOM	VOM	LT	Ramp	Eff.
Units	[M€/GW]	[M€/GW]	[M€/GW-y]	[M€/GWh]	[y]	[%]	[GWhf/Gwhe]
Coal old	1823.8	1809.4	18.3	2.6	40	0.5	2.41
Coal	1823.8	1809.4	18.3	2.3	40	0.5	1.79
CCGT old	899.2	892.1	11.3	1.8	30	0.8	2.49
CCGT	899.2	892.1	11.3	1.6	30	0.9	1.69
Gas CHP	1016.0	1008.0	12.7	1.6	20	0.9	2.89
GT	562.0	557.5	7.0	1.0	20	1	2.81

[52] Not all the countries have all the technologies present. The specific country composition of technologies is extracted from [27].

Technology	Investment 2020	Investment 2050	FOM	VOM	LT	Ramp	Eff.
Units	**[M€/GW]**	**[M€/GW]**	**[M€/GW-y]**	**[M€/GWh]**	**[y]**	**[%]**	**[GWhf/Gwhe]**
Oil	613.5	613.5	7.8	2.6	20	1	3.01
Waste	2254.4	2254.4	112.7	2.6	20	1	3.13
Other RES	3576.9	3191.1	0.0	3.8	20	1	1
Biomass	2657.4	2229.1	42.3	2.6	20	1	2.44
Nuclear	5636.0	5636.0	70.5	6.4	60	0.2	3.12
Hydro	4284.0	4205.1	10.8	1.1	45	1	1
Onshore Wind	1259.7	1074.5	17.2	1.6	20	1	1
Offshore Wind	1830.8	1102.0	186.0	2.1	20	1	1
Solar	764.9	279.1	2.0	0.4	20	1	1
Pumped Hydro	1252.4	1252.4	4.8	0.0	20	1	1.43
Undispatched	NA	NA	NA	3000	NA	1	NA
Interconnection	(220 - 650)	(220 - 650)	(5.5 - 16.25)	0	50	1	1.02

Appendix C Energy System representation in IESA-Opt

In Table 66 we provide the representation of the energy system considered in IESA-Opt. Here you can find all the technologies able to satisfy the demand of each activity considered in the model. There are three types of activities: driver activities, energy activities, and emission activities. The driver activities create the energy requirements which are satisfied by the energy activities. The operation of both activities result in emissions which are accounted by emission activities. The energy system is divided in 7 sectors for the driver activities: Residential, Services, Agriculture, Industry, Transport, EU Power System, and Non-Energy Related Emissions. The energy activities are segregated in: Power, Refineries, Natural Gas, Hydrogen, District Heating and Final Biomass sectors.

Activity	Sector	Type	List of technologies
Electricity demand - Residential	Residential	Driver	Demand
Houses - Residential Flats	Residential	Driver	House with insulation GFE, House with insulation DC, House with insulation B, House with insulation A, House with insulation A+
Houses - Residential Terrace	Residential	Driver	
Houses - Residential Dwellings	Residential	Driver	
Heat LT Houses C-G	Residential	Energy	Boiler Gas, District Heating
Heat LT Houses A,B	Residential	Energy	Boiler Gas, District Heating, Hybrid Heat Pump
Heat LT Houses A+	Residential	Energy	Boiler Gas, Boiler Gas wSolar, District Heating, Hybrid Heat Pump, Electric Heater, Electric Heater wSolar, Electric Heat Pump Air, Electric Heat Pump Air FLEX, Electric Heat Pump GW, Electric Heat Pump GW FLEX, Micro CHP Gas, Micro CHP H2
Electricity demand - Services	Services	Driver	Demand
Space - Services	Services	Driver	Space with insulation GFE, Space with insulation DC, Space with insulation B, Space with insulation A, Space with insulation A+
Heat LT Services	Services	Energy	Boiler Gas Standard, Boiler Gas HR107, Hybrid Heat Pump, Electric Heat Pump Air, Electric Heat Pump Soil, Mini CHP Gas ,

Activity	Sector	Type	List of technologies
			CHP H2
Electricity demand - Agriculture	Agriculture	Driver	Demand
Heat demand - Agriculture Horticulture	Agriculture	Driver	Demand
Heat demand - Agriculture Other	Agriculture	Driver	Demand
Machinery - Agriculture	Agriculture	Driver	Fuel based machinery, Hybrid machinery
Heat LT Agriculture Horticulture	Agriculture	Energy	CHP Gas, Boiler Gas, Geothermal HP, Shallow Soil Energy, Boiler Biomass
Heat LT Agriculture Other	Agriculture	Energy	Co-Digestion Biomass, Boiler Gas
Steel production - Basic Metals Industry	Industry	Driver	Blast Furnace, Blast Furnace wCCS, Hisarna, Hisarna wCCS, ULCOWIN
Non-Ferro production - Basic Metals Industry	Industry	Driver	Hall-Heroult Standard, Hall-Heroult Improved, Hall-Heroult Novel
Ammonia production - Fertilizer Industry	Industry	Driver	Haber Bosch, Haber Bosch wCCS, Haber Bosch New, Haber Bosch New wCCS, Solid State Ammonia Synthesis (SSAS)
High-value chemicals - Chemical Industry	Industry	Driver	Nafta Steam Cracker Standard, Nafta Steam Cracker Standard wCCS, Naphtha Steam Cracker Improved, Naphtha Steam Cracker Improved wCCS, Olefins from Sugar, Olefins from Starch, Olefins from Wood
Other ETS chemicals - Chemical Industry	Industry	Driver	Remaining Chemicals Production Standard, Remaining Chemicals Production Improved
Other ETS - Industry	Industry	Driver	Remaining ETS Industry Standard, Remaining ETS Industry Improved
Other non-ETS - Industry	Industry	Driver	Remaining non-ETS Industry Standard, Remaining non-ETS Industry Improved
Machinery - Industry	Industry	Driver	Fuel based machinery, Hybrid machinery, Electric machinery
Waste Incineration	Industry	Driver	CHP Waste, CHP Waste wCCS
Waste Sewage	Industry	Driver	CHP after gasification of Sewage
Waste Landfill	Industry	Driver	Gasification of Landfill
Heat SHT Industry	Industry	Energy	Boiler Gas, Boiler Gas wCCS, Hybrid Boiler Gas, Hybrid Boiler Gas wCCS, Boiler Coal, Boiler Coal wCCS, Boiler Biomass,

Activity	Sector	Type	List of technologies
			Boiler Biomass wCCS, Boiler H2
Heat HT Industry	Industry	Energy	Boiler Gas, Boiler Gas wCCS, Hybrid Boiler Gas, Hybrid Boiler Gas wCCS, Boiler Coal, Boiler Coal wCCS, Boiler Biomass, Boiler Biomass wCCS, CHP Gas, CHP Gas wCCS, CHP Biomass (S), CHP Biomass (S) wCCS, CHP Biomass (L), CHP Biomass (L) wCCS, Boiler H2
Heat LT Industry	Industry	Energy	Boiler Gas, Boiler Gas wCCS, Boiler Coal, Boiler Coal wCCS, Boiler Biomass, Boiler Biomass wCCS, Heat Pump Gas, Heat Pump Electricity, Geothermal HP, Boiler H2, Direct Heating Electricity, Co-Digestion Biomass
Motorcycles	Transport	Driver	ICE Vehicle, Electric Battery Vehicle
Passenger Cars	Transport	Driver	ICE 2010 norm Vehicle, ICE 130g Vehicle, ICE 95g Vehicle, ICE 70g Vehicle, ICE Hybrid Vehicle, ICE Natural Gas Vehicle, Plug-In Hybrid Vehicle, Electric Battery Vehicle, Electric Battery Vehicle FLEX, Electric Battery Vehicle P2G, Hydrogen Fuel Cell Vehicle
Light-Duty Vehicles	Transport	Driver	ICE 2010 norm Vehicle, ICE 175g Vehicle, ICE 147g Vehicle, ICE 114g Vehicle, Plug-In Hybrid Vehicle, Electric Battery Vehicle, Electric Battery Vehicle FLEX, Hydrogen Fuel Cell Vehicle
Heavy-Duty Vehicles	Transport	Driver	ICE 2010 norm Vehicle, ICE efficient Vehicle, ICE Natural Gas Vehicle, Electric Battery Vehicle, Electric Battery Vehicle FLEX, Hydrogen Fuel Cell Vehicle
Buses	Transport	Driver	ICE Vehicle,

Activity	Sector	Type	List of technologies
			ICE Vehicle Natural Gas, Plug-In Hybrid Vehicle, Electric Battery Vehicle, Hydrogen Fuel Cell Vehicle
Rail	Transport	Driver	Compression Ignition Train, Conventional Electric Train
Intra-EU Aviation	Transport	Driver	Conventional Airplane
Extra-EU Aviation	Transport	Driver	
Inland-Domestic Navigation	Transport	Driver	Heavy Oil Ship, ICE Ship, CNG Ship
International Navigation	Transport	Driver	
nER-GHG Agriculture - CH4 Enteric Fermentation	Other Emissions	Driver	Enteric Fermentation CH4 Emissions
nER-GHG Agriculture - CH4 Manure Management	Other Emissions	Driver	Manure Management CH4 Emissions
nER-GHG Agriculture - N2O Manure Management	Other Emissions	Driver	Manure Management N2O Emissions
nER-GHG Agriculture - N2O Fertilizer	Other Emissions	Driver	Fertilizer N2O Emissions
nER-GHG Product Use - F-gas Refrigeration	Other Emissions	Driver	Refrigeration HFCs Emissions
nER-GHG All - CO2 Others	Other Emissions	Driver	Other CO2 Emissions
nER-GHG All - CH4 Others	Other Emissions	Driver	Other CH4 Emissions
nER-GHG All - N2O Others	Other Emissions	Driver	Other N2O Emissions
nER-GHG All - F-gas Others	Other Emissions	Driver	Other F-gas Emissions
Electricity demand - BN	EU Power System	Driver	Demand
Electricity demand - BU	EU Power System	Driver	Demand
Electricity demand - BT	EU Power System	Driver	Demand
Electricity demand - FI	EU Power System	Driver	Demand
Electricity demand - IT	EU Power System	Driver	Demand
Electricity demand - PT	EU Power System	Driver	Demand
Electricity demand - ES	EU Power System	Driver	Demand
Electricity demand - SK	EU Power System	Driver	Demand
Electricity demand - CZ	EU Power System	Driver	Demand
Electricity demand - PL	EU Power System	Driver	Demand
Electricity demand - AT	EU Power System	Driver	Demand
Electricity demand - CH	EU Power System	Driver	Demand
Electricity demand - FR	EU Power System	Driver	Demand
Electricity demand - SE	EU Power System	Driver	Demand
Electricity demand - IE	EU Power System	Driver	Demand
Electricity demand - BE	EU Power System	Driver	Demand
Electricity demand - DE	EU Power System	Driver	Demand
Electricity demand - DK	EU Power System	Driver	Demand
Electricity demand - NO	EU Power System	Driver	Demand
Electricity demand - GB	EU Power System	Driver	Demand
Electricity BN	EU Power System	Energy	Electricity from Coal old, Electricity from Coal, Electricity from CCGT old, Electricity from CCGT, Electricity from Gas CHP, Electricity from GT, Electricity from Oil , Electricity from Waste, Electricity from Other RES, Electricity from Biomass, Electricity from Nuclear,
Electricity BU	EU Power System	Energy	
Electricity BT	EU Power System	Energy	
Electricity FI	EU Power System	Energy	
Electricity IT	EU Power System	Energy	
Electricity PT	EU Power System	Energy	
Electricity ES	EU Power System	Energy	
Electricity SK	EU Power System	Energy	
Electricity CZ	EU Power System	Energy	
Electricity PL	EU Power System	Energy	
Electricity AT	EU Power System	Energy	

Activity	Sector	Type	List of technologies
Electricity CH	EU Power System	Energy	Electricity from Hydro, Electricity from Onshore Wind, Electricity from Offshore Wind, Electricity from Solar, Pumped Hydro - Storage DE Undispatched Electricity (VOLL), Interconnection between countries
Electricity FR	EU Power System	Energy	
Electricity SE	EU Power System	Energy	
Electricity IE	EU Power System	Energy	
Electricity BE	EU Power System	Energy	
Electricity DE	EU Power System	Energy	
Electricity DK	EU Power System	Energy	
Electricity NO	EU Power System	Energy	
Electricity GB	EU Power System	Energy	
Electricity NL - HVNS	NL Power System	Energy	Electricity from Offshore Wind
Electricity NL - HV	NL Power System	Energy	Electricity from Coal old, Electricity from Co-fired Coal, Electricity from Co-fired Coal wCCS, Electricity from CCGT, Electricity from CCGT wCCS, Electricity from GT, Electricity from Nuclear, Electricity from Biomass, Electricity from Onshore Wind, Electricity from Solar PV Fields, Electricity from Hydro, Undispatched Electricity (VOLL), Compressed Air Aboveground Storage, Compressed Air Underground Storage, Import from BE, Import from DE, Import from DK, Import from NO, Import from GB, Import from NS, Transformer from LV to HV, Transformer from MV to HV
Electricity NL - MV	NL Power System	Energy	Electricity from Industrial Solar PV, Transformer from HV to MV Baseload, Transformer from HV to MV Peaks, Transformer from LV to MV
Electricity NL - LV	NL Power System	Energy	Electricity from Residential Solar PV, Transformer from HV to LV, Transformer from MV to LV Baseload, Transformer from MV to LV Peaks
Heat LT Network	District Heating	Energy	Boiler Gas, Boiler Gas wCCS, Boiler Biomass, Boiler Biomass wCCS, Geothermal Gas HP, Hot water storage tank
Road Fuel	Refineries	Energy	Deep cracking refinery; Deep cracking refinery wCCS; Basic cracking refinery; Basic cracking refinery wCCS; Koch refinery; Koch refinery wCCS; Bioethanol refinery from sugar; Bioethanol refinery from sugar wCCS; Bioethanol refinery from starch; Bioethanol refinery from starch wCCS;

Activity	Sector	Type	List of technologies
			Bioethanol refinery from wood; Bioethanol refinery from wood wCCS; Biodiesel FAME refinery; Biodiesel FAME refinery wCCS; Biodiesel FT refinery from wood; Biodiesel FT refinery from wood wCCS; P2L methanol pathway, ext. H2, DAC; P2L methanol pathway, ext. H2, ext CO2; P2L FT pathway, ext. H2, DAC; P2L FT pathway, ext. H2, ext CO2; P2L methanol pathway, alk. electrolysis, DAC; P2L methanol pathway, alk. electrolysis, ext CO2; P2L FT pathway, alk. electrolysis, DAC; P2L FT pathway, alk. electrolysis, ext CO2
Hydrogen	Hydrogen	Energy	Gas Reforming, Gas Reforming wCCS, Alkaline Electrolyzer, Small scale storage buffer, Large scale storage buffer
Final Natural Gas	Natural Gas	Energy	Gas Extraction, Gas Import, LNG Import, Gas from Manure Digestion, Gas from Manure-Starch Co-Digestion, Gas from Solid Biomass Gasification, Gas from Solid Biomass Gasification wCCS, SynGas from Hydrogen, Small scale storage buffer, Large scale storage buffer
Biomass	Biomass	Energy	From primary to final Biomass
Coal	NL Primary Energy	Energy	Primary form
Crude Oil	NL Primary Energy	Energy	Primary form
Imported Natural Gas	NL Primary Energy	Energy	Primary form
National Natural Gas	NL Primary Energy	Energy	Primary form
Imported LNG	NL Primary Energy	Energy	Primary form
Uranium	NL Primary Energy	Energy	Primary form
Waste	NL Primary Energy	Energy	Primary form
Wet organic matter	NL Primary Energy	Energy	Primary form
Manure	NL Primary Energy	Energy	Primary form
Dry organic matter	NL Primary Energy	Energy	Primary form
Grass crops	NL Primary Energy	Energy	Primary form
Wood	NL Primary Energy	Energy	Primary form
Sugars	NL Primary Energy	Energy	Primary form
Starch	NL Primary Energy	Energy	Primary form
Vegetable Oil	NL Primary Energy	Energy	Primary form
Wind Energy	NL Primary Energy	Energy	Primary form
Solar Energy	NL Primary Energy	Energy	Primary form
Ambient Energy	NL Primary Energy	Energy	Primary form
Geothermal Energy	NL Primary Energy	Energy	Primary form
Solar Heat	NL Primary Energy	Energy	Primary form
Jet Kerosene	NL Primary Energy	Energy	Primary form

Activity	Sector	Type	List of technologies
Heavy Oil for Shipping	NL Primary Energy	Energy	Primary form
Residual Heavy Oil Products	NL Primary Energy	Energy	Primary form
Residual Light Oil Products	NL Primary Energy	Energy	Primary form
Natural Gas Liquids	NL Primary Energy	Energy	Primary form
Coal EU	EU Primary Energy	Energy	Primary form
Oil EU	EU Primary Energy	Energy	Primary form
Gas EU	EU Primary Energy	Energy	Primary form
Nuclear EU	EU Primary Energy	Energy	Primary form
Waste EU	EU Primary Energy	Energy	Primary form
Biomass EU	EU Primary Energy	Energy	Primary form
Heat EU	EU Primary Energy	Energy	Secondary production of EU CHPs
nER-GHG CO2	Emissions	Emission	MACC Components
nER-GHG CH4	Emissions	Emission	
nER-GHG N2O	Emissions	Emission	
nER-GHG F-gas	Emissions	Emission	
CO2 CCUS Network	Emissions	Emission	CO2 Storage, CO2 from Direct Air Capture under ETS scheme, CO2 from Direct Air Capture outside ETS scheme, Small scale storage buffer
CO2 Air ETS	Emissions	Emission	ETS Allowance
CO2 Air n-ETS	Emissions	Emission	CO2 Emission
CO2 Air ETS EU	Emissions	Emission	ETS Allowance
CO2 Air Int. Transport	Emissions	Emission	CO2 Emission

Table 66, Energy System representation in IESA-Opt

Appendix D Scenario Description

Demand volumes

The model requires economic drivers to determine the optimal way in which energy must be supplied. For this purpose, the model considers national economic activities for the residential, services, agricultural, industrial and transport sectors, considering the activities shown in Appendix B for each of the sectors. Also, next to the national economic activities, the model requires the expected demand for electricity in European countries. The sources used to define the scenario presented in this chapter (Table 67) are mainly based on the JRC's POTEnCIA Central Scenario storyline for the Netherlands [42]. JRC's data is complemented with databases from TNO's power dispatch model COMPETES' scenario based on TYNDP Midterm Adequacy Forecasts 2016 and Sustainable Transition scenario [13],[52]; data from PBL's ENSYSI model reference scenario [50]; and the 2019 Netherland's Climate Energy Outlook [75]. The scenario is based on existing policies and measures, and considers GDP growth rates in line with the 2018 Ageing Report [43].

Sector	Driver	Units	Values				Source
			2020	2030	2040	2050	
General	Heat degree days	[HDD]	2900	2800	2700	2600	[76]
Residential	Appliances electricity demand	[PJ]	84.70	88.10	90.50	92.10	[77]
	Number of houses	[Mhouses]	8.2	8.8	9.2	9.6	[77],[50]
Services	Appliances electricity demand	[PJ]	129.9	131.6	133.3	135.0	[77]
	Used space	[Mm^2]	515	540	555	560	[77]
Agriculture	Appliances electricity demand	[PJ]	36.8	38.0	42.5	47.0	[77]
	Heat demand for horticulture	[PJ]	87.2	92.0	96.8	101.5	[77] ,[50]
	Heat demand for agriculture	[PJ]	8.4	8.8	9.2	9.6	[77] ,[50]
	Machinery consumption	[PJ]	22.8	25.3	27.7	30.2	[77]
Industry	Steel production	[Mton]	7.0	6.7	6.8	7.3	[77]
	Aluminium production	[Mton]	0.2	0.2	0.2	0.2	[77] ,[50]
	Ammonia production	[Mton]	2.8	3.0	3.2	3.4	[75]
	HV Chemicals production	[Mton]	7.2	7.7	8.3	8.7	[77] ,[50]
	Other ETS Chem. Industry	[Index]	1.0	1.2	1.3	1.6	[77] ,[50]
	Other ETS Industry	[Index]	1.0	1.0	1.1	1.1	[77] ,[50]
	Other non-ETS Industry	[Index]	1.0	1.0	1.0	1.0	[77] ,[50]
	Machinery consumption	[PJ]	43.0	45.2	47.0	49.5	[77]
Waste	Waste Incineration	[Mton]	7.6	9.1	10.6	12.3	[77] ,[50]
	Waste Sewage	[PJ]	3.7	4.3	5.0	5.6	[50]
	Waste Landfill	[PJ]	0.4	0.1	0.0	0.0	[50]
Transport	Motorcycles	[Gvkm]	5.1	5.9	6.5	7.2	[77]
	Passenger Cars	[Gvkm]	110.5	114.3	119.2	125.3	[77]
	Light-Duty Vehicles	[Gvkm]	21.1	24.3	27.4	32.3	[77]
	Heavy-Duty Vehicles	[Gvkm]	7.4	7.7	8.0	8.3	[77]
	Buses	[Mvkm]	617.2	624.5	637.3	650.0	[77]
	Rail	[Mvkm]	170	200	215	230	[77]
	Intra-EU Aviation	[Mvkm]	210	260	340	430	[77]

	Extra-EU Aviation	[Mvkm]	670	740	790	850	[77]
	Inland-Domestic Navigation	[Mvkm]	55	70	80	90	[77]
	International Navigation	[Mvkm]	110	125	135	145	[77]
Emissions	Other CO_2 Emissions	[MtonCO_2]	26.6	24.0	21.7	19.6	[47,78,79]
Power EU	EU Electricity demand[53]	[EJ]	11.7	11.8	12.0	11.9	[13]

Table 67, Activity volumes considered in the Reference Scenario.

Resources' costs

The model satisfies the need for energy demands by the combination of primary energy supply, conversion of primary energy in final energy and final energy imports. Therefore, the costs assumed for the primary assets supplied to the system are direct input to the model and key part of the scenario definition. It should be noted that the future price levels of commodities are always (very) uncertain. In particular, biomass prices can be volatile depending on the underlying assumptions on scarcity (that drives up prices vs. costs) or strategies to increase availability (e.g., planting of degraded lands and increased agricultural productivity, which can push learning curves and lower the costs).

These primary assets can be distinguished as conventional fuels, biomass sources, and the ETS allowances projected costs. The data for the reference scenario used in this chapter is composed of the following sources and presented in Table 68. First, conventional fuels prices projections are retrieved from POTEnCIA's Central Scenario database [77]. Then, the price projections of the bio-resources are based on ENSPRESO-BIOMASS reference scenario [45]. Finally, the ETS allowance cost projections are retrieved from two sources, the 2019 Netherland's Climate Energy Outlook [75] for the 2020-2030 period, and the CPB high-efficiency scenario projections [80] for the period 2030-2050.

Commodity	**Units**	**Values**				**Source**
		2020	2030	2040	2050	
Coal	[€$_{2019}$/GJ]	3.0	3.7	4.1	4.4	[77]
Oil	[€$_{2019}$/GJ]	10	17	19	20	[77]
Natural gas	[€$_{2019}$/GJ]	7.1	10.3	11.4	11.8	[77]
Imported LNG	[€$_{2019}$/GJ]	7	9	9.7	10	[81]
Imported oil products	[€$_{2019}$/GJ]	12.5	21.2	23.8	25	[77]
Uranium	[€$_{2019}$/GJ]	0.8	0.8	0.8	0.8	[75]
Waste	[€$_{2019}$/GJ]	6.9	7.0	7.0	7.0	[82]
Imported biodiesel	[€$_{2019}$/GJ]	20	35	50	70	[83]
Imported biokerosene	[€$_{2019}$/GJ]	20	26	42	63	[83]
Manure	[€$_{2019}$/GJ]	0.1	0.1	0.1	0.0	[82]
Dry organic matter	[€$_{2019}$/GJ]	4.5	4.2	4.1	4.0	[82]
Grass crops	[€$_{2019}$/GJ]	9.5	8.7	8.4	8.2	[82]

[53] The model requires demand and supply data on the following European countries: United Kingdom, Norway, Denmark, Germany, Belgium, Ireland, Sweden, France, Switzerland, Austria, Poland, Czech Republic, Slovakia, Spain, Portugal, Italy, Finland, and aggregated figures on Baltic countries, Balkan countries within the EU, and Balkan countries outside the EU. The detailed data used can be found in the web portal of the IESA-Opt model [22].

Wood (crops, and others)	[€$_{2019}$/GJ]	16.9	16.9	16.9	16.9	[82]
Imported wood	[€$_{2019}$/GJ]	8.2	7.4	6.9	6.4	[82]
Sugars	[€$_{2019}$/GJ]	4.3	4.6	4.6	4.6	[82]
Starch	[€$_{2019}$/GJ]	15.9	21.3	21.5	21.9	[82]
Vegetable oil	[€$_{2019}$/GJ]	26.5	38.1	38.0	38.0	[82]
Imported vegetable oil	[€$_{2019}$/GJ]	30.5	43.7	43.7	43.7	[83]
ETS allowance	[€$_{2019}$/tonCO$_2$]	22	47	105	160	[75],[80]

Table 68, Costs assumptions considered in the Reference Scenario.

Transition potentials

The potential assumed for technologies to develop has a large influence on the definition of the scenario. Many of these assumed potentials have an important influence in the determination of transitionary costs, notably, potentials for renewable energy sources (including biomass) and CO_2 storage. The reference scenario bases the storylines of these potentials accordingly with the ENSPRESO reference scenario for biomass [45] and the TNO's scenario 'towards a sustainable energy system for the Netherlands' [83]. Table 69 shows the assumed potentials for the reference scenario.

Potential	**Units**	**Values**				**Source**
		2020	2030	2040	2050	
Nuclear power	[GW]	0.48	0.48	0	0	[83]
Offshore wind	[GW]	1.1	14	45	60	[83]
Onshore wind	[GW]	3.5	8	10	12	[83]
Solar PV fields	[GW]	1.1	5	15	30	[83]
Industrial Solar PV	[GW]	2.1	15	30	40	[83]
Residential Solar PV	[GW]	3.5	20	40	60	[83]
Geothermal Energy	[PJ/y]	10	50	125	200	[82]
Waste	[PJ/y]	46	55	64	74	[82]
Wet organic matter	[PJ/y]	3.7	4.3	5	5.6	[82]
Manure	[PJ/y]	72	72	72	72	[82]
Dry organic matter	[PJ/y]	7.4	7.6	8.8	9.5	[82]
Grass crops	[PJ/y]	14.2	27.7	25.7	23	[82]
Wood	[PJ/y]	60	80	100	120	[82]
Imported wood	[PJ/y]	20	120	220	320	[83]
Sugars	[PJ/y]	15.6	23	19.4	15.8	[82]
Starch	[PJ/y]	0.4	0.5	0.5	0.6	[82]
Vegetable Oil	[PJ/y]	0.1	0.4	0.1	0.1	[82]
Storage of CO_2	[MtonCO$_2$/y]	0	7.5	25	50	[83]

Table 69, Potential assumptions considered in the Reference Scenario.

Appendix E Snapshots of the interactive User Interface

The focus of the paper is on modelling trade-offs; therefore, not many energy-related results are presented in the text. Here we present the state of the energy system based on the reference scenario. The figures presented in this appendix can be accessed through the model's online user interface in an interactive way.

Final Energy

The model optimally provides the required energy for each activity based on techno-economic constraints. As a result, the final energy consumed by each sector in 2050 can be tracked in Figure 84. The Industry sector accounts for more than half of the final energy in the Netherlands. Almost half of the energy consumption in Industry is dedicated to feedstock which is used in refineries to satisfy export demands. In the Transport sector, although the model electrifies the whole passenger car fleet, the international aviation and navigation transport rely heavily on fossil fuels. The heat demand in the Agriculture and Residential sectors is met with renewable sources such as electricity, ambient heat, and solar heat.

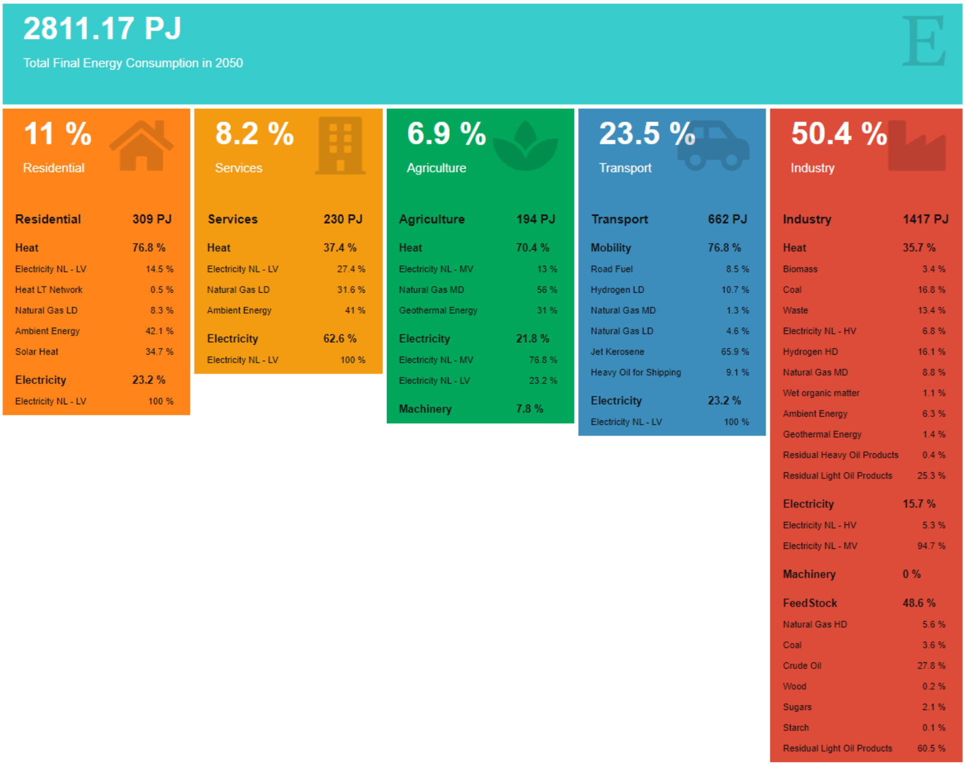

Figure 84, Final energy consumption by sector and energy carrier in 2050.

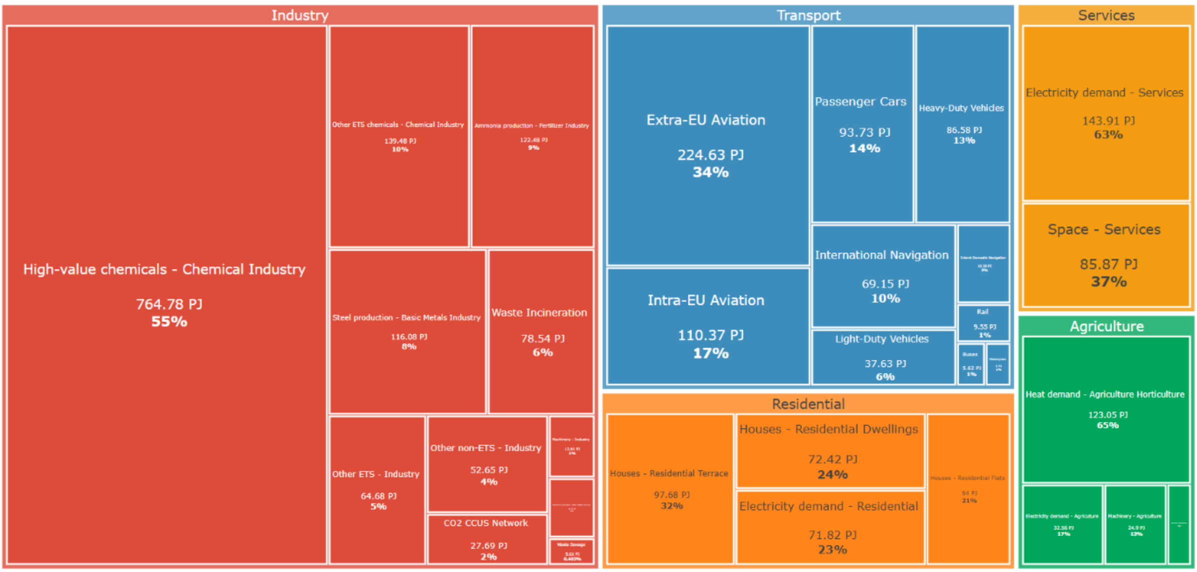

Figure 83, Final energy consumption by each activity in 2050

Activities

The final energy allocation can be represented by sectoral activities as in Figure 83. The main energy consumption in industry is coming from processing high-value chemicals. More than half of the final energy in the Transport sector is consumed by aviation activities, while international navigation stands for only 10 percent. Readers are invited to see the interactive graphs on the online user-interface of the model.

Primary energy mix

Despite the 95% emission reduction policy in Netherlands by 2050, the energy mix shows considerable amount of fossil fuels. These fossil fuels are used to produce exported chemical products. The reference scenario assumes the same amounts of fossil exports as 2020.

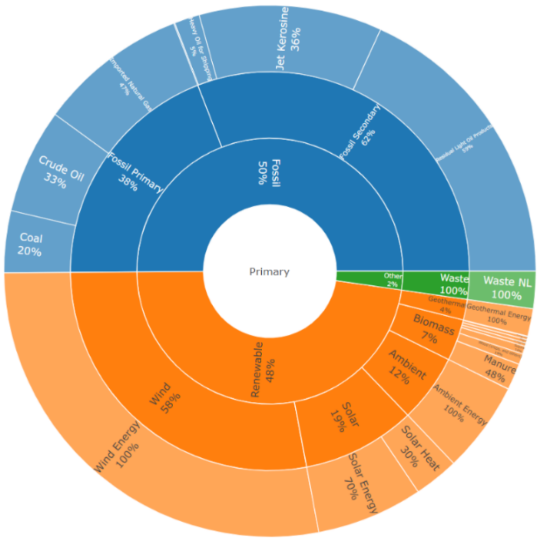

Figure 85, Primary energy mix of the Dutch energy system in 2050

Renewable energy production

The renewable energy is mainly produced by wind farms, notably off shore wind in the North Sea region. Moreover, solar energy capacity increases considerably. However, due to the lack of space in the Netherlands, the solar energy production growth stops after 2040. After 2040, the solar thermal technology option starts to grow, as it can use the rooftops of residential buildings. Also, the ambient energy grows considerably that refers to higher installation of heat pumps.

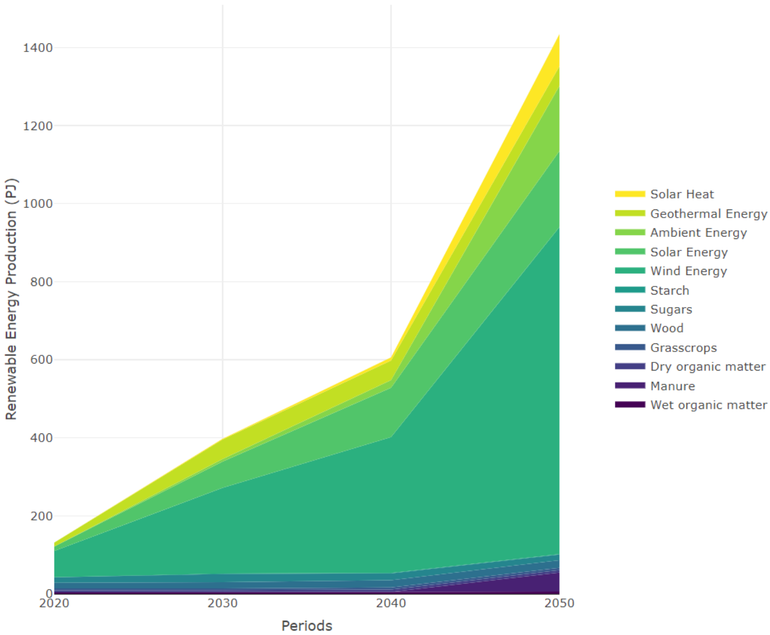

Figure 86, Renewable energy production transition by source. Wind energy dominates in all periods.

Sankey

A major added value of an integrated energy system model is the capability to analyze the inter-sectoral effects. The Sankey diagram in Figure 85 demonstrates the energy flows in 2050. The electricity is mainly produced by Wind, Solar, Import from EU, Natural Gas, and Biomass. The electricity can be used to produce Hydrogen (e.g. electrolysis), Natural Gas (i.e. P2Gas), Liquids (i.e. P2Liquids), and Heat (i.e. P2Heat). Chemical liquids play a major role in the energy system of the Netherlands. These liquids are either Imported (by the reference scenario assumption) or produced by (mostly) electricity. Therefore, relative emissions are minimized.

In order to keep the diagram minimal, we did not include the flow numbers. Readers are invited to visit the online platform of the IESA-Opt model to see the interactive graph.

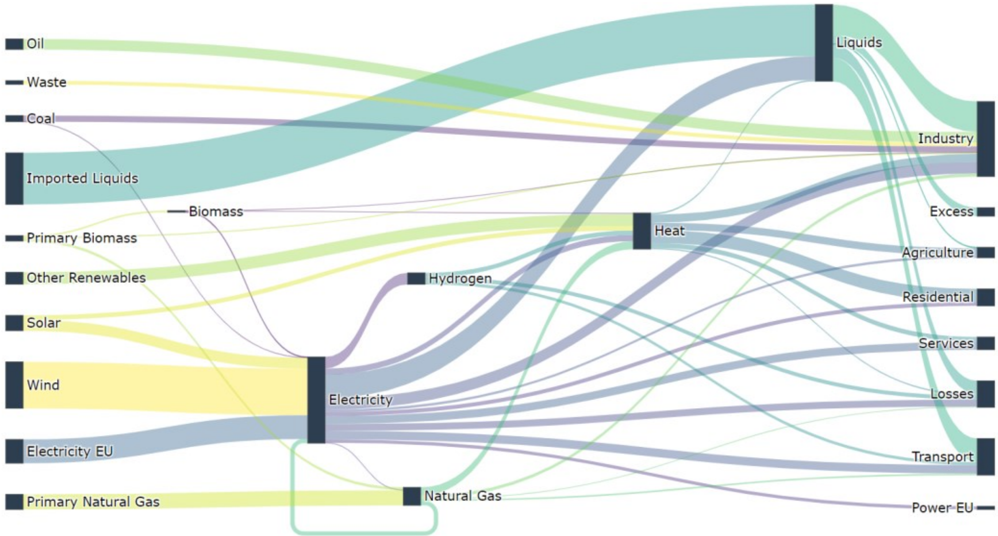

Figure 87, Energy flow Sankey diagram in 2050.

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Summary

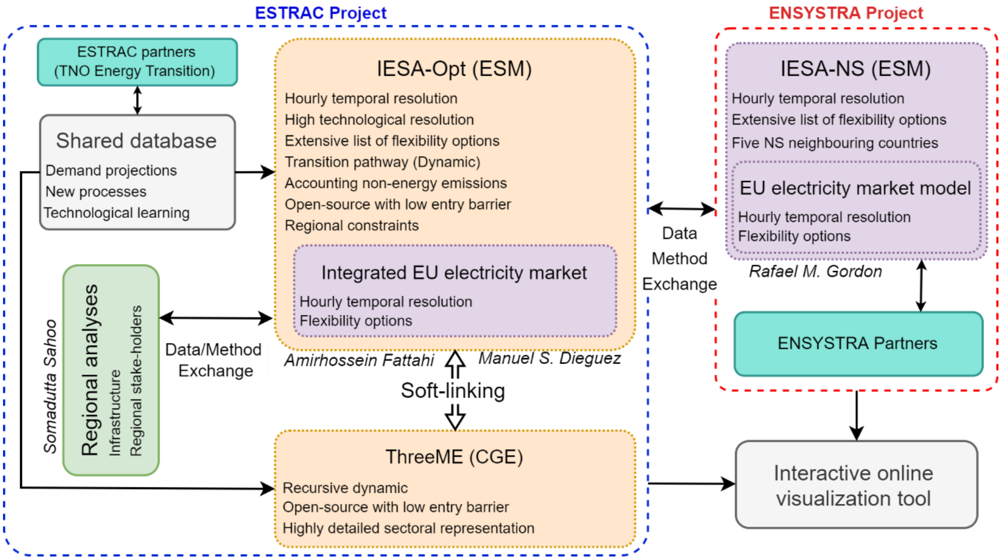
Energy System Models (ESMs) have been developed to guide decision-makers in making long-term robust policy decisions toward low-carbon energy system transition. However, many ESMs lack specific capabilities for adequately addressing this transition. This lack of capabilities affects the quality of the national energy transition scenarios. This thesis aimed to improve national energy system modeling capabilities and demonstrate its impact on Dutch energy transition scenarios.

We started by identifying energy system modeling gaps by taking into consideration expected elements of energy transition. This includes greatly increased use of low-carbon energy sources (such as wind, solar, geothermal, and nuclear power) and new energy carriers (e.g., hydrogen, ammonia, and synthetic fuels). To make the best use of these energy sources we must implement sector coupling (e.g. Power to Heat (P2Heat), Power to Mobility (P2Mobility), Power to Liquids (P2Liquids), and Power to Gas (P2Gas)), storage solutions (e.g. batteries, seasonal thermal energy storage (TES), and compressed air energy storage (CAES)), and demand-side management (e.g. demand response and demand shedding). Furthermore, smarter infrastructure management (such as collective heat networks, smart power distribution, and hydrogen pipelines), and increased social involvement (through prosumers and decentralized generation) must be put in place. Moreover, it is crucial that the entire carbon balance is considered, including energy and non-energy related emissions (such as enteric fermentation, fertilizers, and manure management) and carbon removal schemes, such as, afforestation, bioenergy carbon capture and storage (BECCS), and direct air capture (DAC). In addition, this transition can have a major impact on the whole economy as capital and labor flows are redirected toward the elements mentioned.

Then, based on policy needs and the identified gaps, we proposed a conceptual modeling suite, IESA, to bridge major energy system modeling gaps. Moreover, we developed a state-of-the-art optimization ESM, IESA-Opt, to better model the energy system transition of the Netherlands. Further, we demonstrated the impact of higher modeling capabilities on national energy transition policies, for instance, the role of nuclear power. Finally, to cover the macroeconomic impacts of the energy transition, we closed the IESA suite by soft-linking IESA-Opt and an advanced computable general equilibrium model, namely, ThreeME.

Furthermore, we provided an open-source and user-friendly ESM with a corresponding database that lowers the entry barrier to the energy system modeling field. Moreover, we designed and implemented an interactive online user interface to present model results. Furthermore, we collaborated with the ENSYSTRA project by co-developing the IESA-NS

model. The developed tools and software in the present research have provided insights and enabled several other researchers and Ph.D. and master students to conduct their research effectively. The result of the general approach that was presented in the Introduction section is presented in the following figure.



The main contributions and outcomes of the present dissertation can be summarized:

6. We developed a state-of-the-art integrated energy system framework (i.e., IESA).
7. We demonstrated the impact of advanced modeling capabilities on Dutch energy transition scenarios.
8. Using the IESA framework, we linked energy system analysis with macroeconomics and policy.
9. We laid a novel energy system modeling framework with a low entry barrier.
10. We showed that an efficient use of computational capacity and a lean methodology could open doors to analyses that were left unexplored.

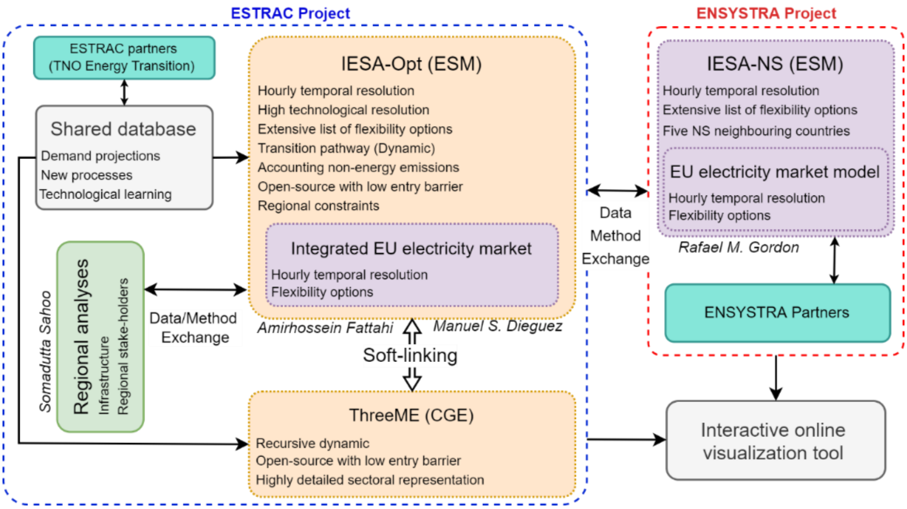
Samenvatting

Energie Systemen Modellen (ESM's) zijn ontwikkeld om beleidsmakers te begeleiden bij het nemen van langetermijnbeslissingen voor een overgang naar een koolstofarm energiesysteem. Echter, veel ESM's missen specifieke mogelijkheden om deze overgang adequaat aan te pakken. Dit gebrek aan mogelijkheden heeft invloed op de kwaliteit van de nationale energietransitie scenario's. Het doel van dit proefschrift was om de mogelijkheden voor nationale energiemodellering te verbeteren en de impact ervan op de Nederlandse energietransitie scenario's te demonstreren.

We begonnen met het identificeren van hiaten in energiemodellering door rekening te houden met verwachte elementen van de energietransitie. Dit omvat een sterkere inzet van koolstofarme energiebronnen (zoals wind, zon, geothermie en kernenergie) en nieuwe energiedragers (bijvoorbeeld waterstof, ammoniak en synthetische brandstoffen). Om optimaal gebruik te maken van deze energiebronnen moeten we sectorintegratie implementeren (zoals Power to Heat (P2Heat), Power to Mobility (P2Mobility), Power to Liquids (P2Liquids) en Power to Gas (P2Gas)), opslagoplossingen (zoals batterijen, seizoensgebonden thermische energieopslag (TES) en persluchtenergieopslag (CAES)), en vraagbeheer (zoals vraagrespons en vraagvermindering). Bovendien moeten we slimmer infrastructuurbeheer (zoals collectieve warmtenetten, slimme elektriciteitsdistributie en waterstofleidingen) en verhoogde maatschappelijke betrokkenheid (via prosumenten en gedecentraliseerde opwekking) implementeren. Bovendien is het cruciaal dat de gehele koolstofbalans wordt overwogen, inclusief energiegerelateerde en niet-energiegerelateerde emissies (zoals enterische fermentatie, meststoffen en mestbeheer) en koolstofverwijderingsschema's, zoals bebossing, bio-energie koolstofafvang en -opslag (BECCS) en directe luchtafvang (DAC). Bovendien kan deze overgang een grote impact hebben op de gehele economie, omdat kapitaal- en arbeidsstromen worden omgeleid naar de genoemde elementen.

Vervolgens hebben we, op basis van beleidsbehoeften en de geïdentificeerde hiaten, een conceptueel modelleringspakket voorgesteld, IESA, om belangrijke hiaten in energiemodellering te overbruggen. Bovendien hebben we een geavanceerd optimalisatiemodel, IESA-Opt, ontwikkeld om de energietransitie van Nederland beter te modelleren. Verder hebben we de impact van geavanceerde modelleringsmogelijkheden op nationaal energiebeleid gedemonstreerd, zoals de rol van kernenergie. Ten slotte hebben we de IESA-suite afgesloten door IESA-Opt en een geavanceerd evenwichtsmodel voor de algemene economie, genaamd ThreeME, via een zachte-koppeling te verbinden om de macro-economische gevolgen van de energietransitie te dekken.

Bovendien hebben we een open-source en gebruiksvriendelijk ESM geleverd met een bijbehorende database die de toegang tot het veld van energiemodellering verlaagt. Bovendien hebben we een interactieve online gebruikersinterface ontworpen en geïmplementeerd om de resultaten van het model te presenteren. Daarnaast hebben we samengewerkt met het ENSYSTRA-project door het gezamenlijk ontwikkelen van het IESA-NS-model. De ontwikkelde tools en software in het huidige onderzoek hebben inzichten geboden en het voor andere onderzoekers, promovendi en masterstudenten mogelijk gemaakt om hun onderzoek effectief uit te voeren. Het resultaat van de algemene aanpak die werd gepresenteerd in de Inleiding wordt gepresenteerd in de onderstaande figuur.



De belangrijkste bijdragen en resultaten van dit proefschrift kunnen als volgt worden samengevat:

1. We hebben een geavanceerd geïntegreerd energiesysteemframework ontwikkeld (d.w.z. IESA).
2. We hebben de impact van geavanceerde modelleringsmogelijkheden op Nederlandse energietransitie scenario's gedemonstreerd.
3. Met behulp van het IESA-framework hebben we energie systeemanalyse gekoppeld aan macro-economie en beleid.
4. We hebben een nieuw energiemodelleringsframework gebouwd met een lage instapdrempel.
5. We hebben aangetoond dat een efficiënt gebruik van rekenkracht en een Lean-methodologie deuren kunnen openen voor analyses die onontgonnen waren gebleven.

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