Frigg 2.0: Integrating price-based demand response into large-scale energy system analysis

Amos Schledorn[a,*], Sandrine Charousset-Brignol[b], Rune Grønborg Junker[a], Daniela Guericke[c], Henrik Madsen[a,d], Dominik Franjo Dominković[a]

[a] *Department of Applied Mathematics and Computer Science, Technical University of Denmark*
[b] *Electricité de France*
[c] *Department of High-tech Business and Entrepreneurship, University of Twente*
[d] *Norwegian University of Science and Technology (ZEN-Project)*

Abstract

Transitioning energy systems to renewable sources requires a paradigm shift in system operation: Rather than only dispatching central generators to match volatile demand, the demand side must also be adjusted flexibly to match renewable generation. Electrified heating is one source of such flexibility, via demand response and heat storage.

In energy system analysis, demand response is often modelled as a direct control problem, where central decisions set demand levels. We consider this an over-simplification and have previously proposed Frigg, a framework for integrating price-based indirect demand response models in energy system analysis. In this article, a reformulation is proposed that solves central previous shortcomings, such as modelling a larger number of intertemporal constraints. This allows wide application of Frigg in energy system modelling.

In this paper, Frigg is applied to soft-link plan4EU, a European electricity dispatch model, and the Flexibility Function. Based on this modelling setup, we conduct a case study on the role of power-to-heat demand flexibility, in the form of demand response and heat storage, in the Danish electricity system of 2050.

Our results highlight the significance of Denmark as an electricity transit country: We find that power-to-heat demand response offers mild cost savings in the Danish electricity system, mainly through lower-cost electricity imports and higher-cost exports. Similarly, heat storage allows utilisation of the Danish geographical position. Heat storage achieves significantly higher savings than only demand response. Combining heat storage with demand response achieves similar operational savings but lowers heat-storage investment costs, leading to an overall cost reduction of approximately 7% in 2050.

Keywords: Frigg, plan4EU, Demand response, Energy system optimisation, Power-to-heat

Nomenclature

Sets	
$\mathcal{T}$	Set of time steps t
$\mathcal{U}$	Set of generators u
$\mathcal{I}$	Set of pieces i of piece-wise linear function approximation
Parameters	
$C_{u,t}$	Variable generation cost of unit u in time step t [EUR/MWh]
C^{INV}	Annualised heat storage investment cost [EUR/MWh/a]
$\overline{q}_{u,t}$	Generation capacity of unit u in time step t [MWh]
$\underline{q}_{u,t}$	Minimum generation quantity of unit u in time step t [MWh]
D_t	Inflexible electricity demand in time step t [MWh]
Δ	Maximum (normalised) welfare loss through demand response
P^{el}	Slack electricity generator penalty cost [EUR/MWh]
P^{h}	Slack heat generator penalty cost [EUR/MWh]
ϕ	Coefficient of performance of electrified heat generators [EUR-heat/EUR-el]
$\overline{\sigma}$	Maximum storage level (generic energy carrier) [MWh]
$\overline{\sigma}^{\text{El}}$	Maximum storage level (electricity storage) [MWh]
β_i^0	Intercept of piece i of piece-wise linear model
$\beta_i^{\text{B}}\left(\beta_i^{\text{u}}/\beta_i^{\text{X}}\right)$	Coefficient of piece i and regressor B_t (u_t/x_t) of piece-wise linear model
$\underline{B}_i^{\text{B}}\left(\underline{B}_i^{\text{u}}/\underline{B}u_i^{\text{X}}\right)$	Start point of B (u/X) in piece i of piece-wise linear model
$\overline{B}_i^{\text{B}}\left(\overline{B}_i^{\text{u}}/\overline{B}u_i^{\text{X}}\right)$	End point of B (u/X) in piece i of piece-wise linear model
$\overline{y} \in \mathbb{R}$	Heat capacity (combined wattage of heat pumps and electric boilers)
Variables	
$q_{u,t} \in \mathbb{R}_0^+$	Energy generation of heat unit u in time step t [MWh]
$\sigma_t \in \mathbb{R}_0^+$	State of charge of (generic energy carrier) storage at time step t [MWh]

*amosc@dtu.dk

$\sigma^0 \in \mathbb{R}_0^+$	Initial state of charge of (generic energy carrier) storage [MWh]
$\sigma_t^+ \in \mathbb{R}$	Inflow to (generic energy carrier) storage [MWh] in time step t
y_t	Post-response demand in time step t [MWh]
$\sigma_t^{el}(\sigma_t^h) \in \mathbb{R}_0^+$	State of charge of electricity (heat) storage at time step t [MWh-el (MWh-heat)]
$\sigma^{el0}(\sigma^{h0}) \in \mathbb{R}_0^+$	Initial state of charge of electricity (heat) storage [MWh-el (MWh-heat)]
$\sigma_t^{el+}(\sigma_t^{h+}) \in \mathbb{R}$	Inflow to electricity (heat) storage in time step t [MWh-el (MWh-heat)]
$\overline{\sigma}^h \in \mathbb{R}$	Heat storage capacity [MWh-heat]
$\alpha_{i,t} \in \{0, 1\}$	1 if piece i of piece-wise linear approximation is active in time step t, 0 otherwise
$\tilde{B}_{i,t}(\tilde{u}_{i,t}, \tilde{x}_{i,t}) \in \mathbb{R}$	Contribution of piece i to B_t (u_t/x_t) in piece-wise linear model in time step t
$B_t \in \mathbb{R}$	Baseline heat demand in time step t
$u_t \in \mathbb{R}$	Price of electrified heat in time step t
$x_t \in \mathbb{R}$	State of demand response in time step t
$\delta_t^{el}(\delta_t^h) \in \mathbb{R}_0^+$	Slack generation of electricity (heat) in time step t
Demand response model	
B_t	Baseline demand in time step t
x_t	State of demand response in time step t
u_t	Indirect control signal (price) in time step t
C	Demand response capacity (energy required to increase x_t from lowest to highest possible value)
$f : (B_t, x_{t-1}, u_t) \to \mathbb{R}$	State function
$g : (B_t, x_t, u_t) \to \mathbb{R}$	Demand as a function of price, state and baseline demand

1. Introduction

Under its "Fit for 55" package, the European Union (EU) aims to reduce emissions by no less than 55% by 2030 and to be climate neutral by 2050 [1]. There are few "must-have" technologies for achieving these targets [2], but energy storage and other flexibility sources are central in this process [3] as they enable integration of larger amounts of renewable energy [4].

Denmark shares the same 2050 target as the EU, but aims at higher reductions in 2023, with 70% compared to 1990 [5]. Meeting this target requires transforming the Danish electricity system to low-carbon [6] and coupling it more strongly to the other sectors of the country's energy system [7]. One aspect of the Danish green transition is to increase the deployment of electrified heating (power-to-heat) [6], which, if powered by renewable electricity, reduces emissions in the heating sector and, paired with demand flexibility, can have a balancing effect on the electricity system [8]. In the Danish district heating sector, which supplies more than 60% of the country's heat customers [9], the Danish Energy Agency expects heat pump capacity to increase from less than 100 MWh in 2018 to more than 800 MWh in 2030 [6].

Heating technologies, energy storage, and demand response, along with cross-border electricity exchange, constitute the main sources of flexibility in energy systems [10]. Heat pumps and intelligent heat storage specifically have been found to improve system efficiency [11]. Thus, an adequate representation of heat-demand flexibility, namely heat storage and demand response, in energy system analysis is crucial in providing decision support [12]. However, end-consumer behaviour is traditionally not included in energy system modelling [13], where demand is mostly modelled as a fixed input rather than a model variable [14]. However, demand response can improve system flexibility significantly [15] and the choice of flexibility options in energy system models can significantly impact study results [16].

The rest of this paper is organised as follows: Section 2 summarises related work. The modelling setup is introduced in Section 3, followed by a case study description and results in Section 4. Finally, Section 5 provides a conclusion and an outlook on future work.

2. Related work and contribution

2.1. Methodologically related work

In this study, we propose a novel soft-linking approach for integrating price-based demand response models in large-scale energy system analysis. Examples of soft-linking approaches in energy system modelling are reviewed in Section 2.1.1 and an overview of demand response modelling approaches is given in Section 2.1.2.

2.1.1. Soft-linking approaches in large-scale energy system analysis

Model coupling is becoming increasingly popular in the field of energy system analysis, as many studies require detailed analyses that a single model alone might not capture. We review a selection of such approaches in the following section and refer the reader to [17] for a more detailed overview.

Some studies couple an energy system model to a, typically, less detailed model of the entire economy. For instance, [18] propose a soft-linking approach for integrating a top-down macroeconomic model and a bottom-up energy system model for Denmark. [19] propose a soft-linking setup of an integrated assessment model to a global power system model.

Other setups couple an energy system model and a more detailed sector-specific model: [20] soft-link the JRC-EU-TIMES model with a simulation model of the EU transport sector. [21] couple a capacity expansion model of the British electricity system with an investment model for hydrogen infrastructure. [22] link a transport network model with a vehicle fleet model and a TIMES model of the Norwegian energy system. [23] analyse the role of zero-emission neighbourhoods in transition pathways of the electricity and heat system by coupling EMPIRE, a capacity expansion model of the European electricity and heat system, with ZENIT, an investment model for zero-emissions neighbourhoods. A framework for soft-linking an energy planning model to power flow analysis is proposed in [24]. The authors analyse a system of interconnected islands and conclude that higher temporal, and especially spatial model resolution significantly improves modelling results.

Demand response is often analysed in localised studies, such as in [25], who link a unit commitment model of a district heating system with a space heating model and apply it in a case study on the city of Gothenburg, Sweden. They find that demand response evens out demand fluctuations and decreases costs of heating. [26] propose a demand response model that operates based on the electricity price differential between two consecutive hours. They link this model to an electricity system model to analyse the cost savings potential of demand response in an island system. In [27], which our study partly builds on, a capacity expansion model of the district heating system of Zagreb is soft-linked with the Flexibility Function[28, 29], the same demand response model applied in the present study. However, their approach does not allow any notion of (near-) optimality.

2.1.2. *Demand response modelling approaches*

Demand response can be considered a direct or indirect control problem [30]. Direct control is often modelled as shiftable load (e.g. [31]) or energy storage (e.g. [32]). Indirect control means that consumers are incentivised to adjust their consumption through remuneration schemes or through time-varying prices [33]. Energy system optimisation models, often formulated as (mixed-integer) linear programs [13] tend to consider demand levels fully exogenous [14] or assume direct control of flexible demand (e.g. [32]). Modelling demand response as a direct control problem can ease the modelling task, since it might not lead to a higher problem class (staying (mixed-integer) linear) [12]. A lower problem class, in turn, can reduce the model's solution time [34]. However, demand is not directly controllable in practice [35], which raises the question of how to represent it in energy system modelling.

While several studies exist that analyse demand response in energy systems or propose related soft-linking approaches, literature that a) models price-based demand response, b) optimises its control, and c) integrates it in a generic way in energy system planning models seems to be sparse.

Frigg, a first approach to this problem, was proposed in [12], which we extended in this study. Despite successfully integrating demand response into energy system optimisation, the backward dynamic programming approach in [12] scales badly with a larger number of intertemporal constraints, such as energy storage or investments. It also does not account for the costs of providing demand response in the form of consumers' unwillingness to be flexible. Both shortcomings are addressed in the present study.

2.2. *Demand response potential of Danish electrified heating*

Some previous studies explicitly analyse demand flexibility in Denmark: In [36], the demand response potential of the Danish power system is estimated based on the output of several other studies as a "total potential peak load reduction" to be 704-1409MW, of which 85-172 MW come from residential water and space heating. The authors of [37] study demand response from electrified heating on the island of Bornholm, Denmark. They find that demand response reduces social costs by 5.4% and increases the uptake of renewable energy sources (RES) by 8.6%. [38] analyse the impact of demand response from different electricity demand sub-sectors, excluding heating, in a future Danish power system. They highlight international exchange as the most sensitive parameter, with imports and exports being reduced by 0.25 TWh and 0.81 TWh, respectively. As for this study, [32] tackle power-to-heat flexibility, but assume direct demand response control. The authors analyse the role of individual heat pumps in wind power integration for the 2020 Danish energy system with 50% wind power. They include demand response from building envelopes as directly controllable passive heat storage. The authors find that heat pumps contribute to wind power integration and that passive heat storage is a cost-effective complement. In a succeeding study, Hedegaard and Münster [11], using the Balmorel model of the Northern European power and heat systems for 2030, conclude that in the Danish energy and heating system, individual heat pumps increase the uptake of wind power and reduce the need for peak power capacity. The authors also find passive heat storage to be economically feasible and recommend related incentives to building owners, since the benefit of peak power capacity reduction needs to be transferred to building owners. Also using Balmorel, [39] analyse power-to-heat flexibility in the Northern European energy system of 2030. They find that power-to-heat increases both RES uptake and electricity prices, thus improving RES profitability.

Other studies do not focus explicitly on power-to-heat or demand flexibility but still include it in their analysis of the Danish energy system. For instance, [7] propose a strategy for a decarbonised Danish energy system by 2045. They find sector integration, including the integration of the heat and power sector, to be one of five cross-cutting areas. Their results suggest investing in heat storage equivalent to the heating demand of one average day and RES balancing through flexible consumption. [40] model transition pathways for the Greater Copenhagen Area, Denmark, and suggest power-to-heat technologies, combined with heat storage, municipal waste and waste heat as the main sources of heat in the future.

2.3. *Contributions*

To the best of our knowledge, existing research does not represent demand response as an indirect control problem in large-scale energy system models. Yet, intelligent coupling of the heat and power sector, including demand response, is expected to play a key role in Denmark's and Europe's green transition. This raises the questions of how to adequately model demand response in large-scale studies and what the role of power-to-heat demand flexibility would be under such an approach.

Based on this research gap, the contributions of this study are two-fold:

1. We propose a new version of Frigg, a modelling approach for soft-linking a price-based demand response model alongside other flexibility sources and a large-scale energy system model. This version allows better modelling of intertemporal constraints, such as investments and energy storage, which is essential in energy system optimisation.
2. We apply this method to a case study of a Danish electricity system of 2050, mostly powered by variable renewable energy sources (VRES) and supplying a large share

of electrified heating. We analyse the cost-savings potential of power-to-heat demand response and heat storage, and we analyse how these savings are achieved.

3. Methodology

In the following, the overall soft-linking framework applied in this study is illustrated in Section 3.1. plan4EU is briefly introduced in Section 3.2, followed by a short description of the Flexibility Function in Section 3.3. The new formulation of Frigg is presented in Section 3.4.

3.1. Soft-linking framework

In this study, we propose an update to Frigg, a first version published in [12], and couple it to plan4EU, a dispatch model of the European electricity system (Section 3.2). Frigg is a soft-linking framework for integrating energy system models and price-based demand response models. The price-based demand response model applied in this study, as in [12], is a Flexibility Function (see Section 3.3), consisting of a set of ordinary, non-linear, differential equations that model end-consumer demand as a function of the price of (some commodity of) energy and a state variable that captures how responsive consumers have been in the past.

The approach proposed in [12] applies backward dynamic programming to solve an economic dispatch problem, where the state of demand response (Section 3.3) is the only state variable. The shortcoming of this approach is poor computational scaling in case additional inter-temporal constraints, i.e. state variables, such as energy storage need to be modelled. The model proposed in this paper also resembles a traditional economic dispatch model, but with the addition of storage investments. We modify the demand balance of the dispatch model by turning energy demand into a variable, rather than a parameter, and we define it as the output of the price-based demand response model. Since said model is non-linear, we apply a piece-wise linear approximation, which, with the addition of binary variables, makes it possible to solve the dispatch problem as a mixed-integer linear program. Note that, while this paragraph discusses "energy" in general, this study is concerned with electricity and heat.

The model workflow in this study is as follows:

1. **Baseline European electricity dispatch – plan4EU:** plan4EU is run with no modifications to the reference case, which is based on case study 1 of the openENTRANCE project [41]. Marginal costs of electricity in this run are used as import prices in the subsequent Frigg runs.
2. **Demand response optimisation for Danish electrified heating – Frigg:** Based on the same input data as the reference case and its output, a simplified electricity and heat dispatch for the Danish system is solved using Frigg, including demand response from electrified heating, modelled via a piece-wise linear approximation of the Flexibility Function. The outputs of this model are power-to-heat demand trajectories and heat storage capacities.
3. **Simulation of demand response – Flexibility Function:** The Flexibility Function simulates end-consumer responses to the prices determined by Frigg. This step makes sure that the demand applied in the succeeding plan4EU run is an output of the actual Flexibility Function rather than its approximation.
4. **Danish electricity and heat dispatch – Frigg:** With electrified heat demand fixed to the output of the Flexibility Function, Frigg is run again, now as a linear program, since the piece-wise approximation of the Flexibility Function is not needed.
5. **Post-flexibility European electricity dispatch – plan4EU:** Demand trajectories for electrified heating after application of demand response and heat storage are passed to plan4EU, which is run again to determine a European electricity dispatch after application of Danish heat demand flexibility.

3.2. plan4EU

plan4EU [42] is a model aimed at optimising and simulating the European electricity system. It is composed of three different hierarchical and embedded layers:

- Capacity expansion,
- Seasonal storage evaluation,
- Unit commitment.

In this work, the seasonal storage and unit commitment layers are used in order to evaluate operational expenditures (OPEX) of the European electrical system by simulating its operation on a typical one-year period, at hourly granularity, taking into account uncertainties in demand, inflows to hydro reservoirs and renewable electricity generation across 37 climatic years.

The unit commitment model computes a (near)-optimal schedule for all assets, ensuring technical constraints are not violated, and demand is fulfilled at each time step in each region at minimum cost. Unit commitment includes modelling of various assets of the system: power plants, demand-side, short-term storage (mainly pumped hydro and batteries) and transmission lines between regions. It also computes the marginal costs of demand and transmission capacity constraints, for all regions and all lines. The seasonal storage valuation model computes optimal strategies for using seasonal water reservoirs. This model uses the above unit commitment model at each step as an evaluation tool.

plan4EU covers the EU 27, as well as the United Kingdom, Norway, Switzerland and Turkey. A methodological description can be found in [43], main equations are formulated in [44].

3.3. Flexibility Function

The demand response applied in this study is based on [27], with parameters chosen identically, if not indicated otherwise. The model is a Flexibility Function[28, 29] of the Danish electrified heating sector.

The state variable X_t captures how responsive consumers have been in the past. Its evolution is governed by the state function formulated in Eq. 1.

$$\frac{\mathrm{d}X_t}{\mathrm{d}t} = \frac{1}{C}(Y_t - B_t) \tag{1}$$

X_t corresponds to the amount of energy "stored" in demand response, which increases if $Y_t > B_t$ and decreases if $Y_t < B_t$, with B_t corresponding to the baseline energy demand in time step t and Y_t being the post-response demand level. The degree of the change in X_t is set by the parameter C, which, in this study, corresponds to the maximum amount of energy that can be "stored" in the system via demand response. Hence, higher values of C correspond to a more flexible system, as the same per-unit change in demand levels triggers a lower per-unit change in the state X_t

The energy demand Y_t is described by a function g (Eq. 2). There, u_t is a price signal (price of energy) in time step t. The price signal constitutes the main (indirect) control variable.

$$Y_t = g(u_t, X_t, B_t) \tag{2}$$

The function g takes the same form as in [12] and is extensively discussed in [27]. As in [12], we slightly modify the model in [27], such that the parameter ϕ is scaled when modifying the demand response capacity C.

Note that the Flexibility Functionis modelled on normalised data such that $X_t, Y_t, B_t \in [0,1]$ and $u_t \in [-1,1] \quad \forall t \in \mathcal{T}$. This transformation is inherently expressed in the formulation in [27] and we convert both Y_t and B_t to and from their normalisation in the implementation of our model in Eq. 7 without stating that conversion explicitly.

3.4. Frigg

Classic economic dispatch. The classic economic dispatch problem of determining the optimal generation quantities $q_{u,t}$ for generators (of some energy commodity) $u \in \mathcal{U}$ in time step $t \in \mathcal{T}$ to satisfy some demand D_t can be written as Eq. 3. The objective is cost minimisation of generation costs, summing the product of variable generation costs $C_{u,t}$ and generation quantity $q_{u,t}$ over all time steps t and generators u (Eq. 3a). In each time step t, the total generation $\sum_{u \in \mathcal{U}} q_{u,t}$ must supply demand D_t and storage inflow λ_t. Equation 3c ensures that all generators stay within their capacity limits $\overline{q}_{u,t}$ at all times. The state of charge of energy storage is described by σ_t, its evolution governed by net storage inflow λ_t, taking positive values for charging and negative values for discharging (Eq. 3d). The state of charge at the beginning of the optimisation horizon is denoted by σ^0, whereas the time steps are assumed to start with 1, i.e., $\mathcal{T} = \{1, 2, ...\}$ (Eq. 3e). Storage operation is further bound by storage capacity $\overline{\sigma}$ (Eq. 3f). Generators have variable (and time-varying, to account for e.g. for electricity imports and exports) production costs $C_{u,t}$ and (variable, to account for VRES) generation capacities $\overline{q}_{u,t}$.

$$
\begin{aligned}
\min \quad & \sum_{t \in \mathcal{T}} \sum_{u \in \mathcal{U}} C_{u,t} q_{u,t} && && \text{(3a)} \\
\text{s.t.} \quad & \sum_{u \in \mathcal{U}} q_{u,t} = D_t + \lambda_t && \forall t \in \mathcal{T} && \text{(3b)} \\
& \underline{q}_{u,t} \leq q_{u,t} \leq \overline{q}_{u,t} && \forall u \in \mathcal{U}, t \in \mathcal{T} && \text{(3c)} \\
& \sigma_t = \sigma_{t-1} + \lambda_t && \forall t \in \mathcal{T} \setminus \{1\} && \text{(3d)} \\
& \sigma_t = \sigma^0 + \lambda_t && t = 1 && \text{(3e)} \\
& \sigma_t \leq \overline{\sigma} && \forall t \in \mathcal{T} && \text{(3f)}
\end{aligned}
$$

Economic dispatch under general (non-linear) Demand Response. The problem in Eq. 3 considers energy demand a parameter. If we assume some part of demand to be flexible, depending on a time-varying price (Section 3.3), demand has to be treated as a variable, as formulated in Eq. 4. Here, we do not assume a specific demand response model, but only post-response demand y_t to be described by some (potentially non-linear) function $g(B_t, x_t, u_t)$, where u_t is some price signal (Eq. 4h). The variable x_t describes a state, the evolution of which is governed by a state function $f(B_t, x_{t-1}, u_t)$ in Eq. 4g. The post-response demand y_t, the state x_t and price signal u_t are normalised ranging from 0 to 1 and -1 to 1 respectively (c.f. Section 3.3). The bounds of the latter two are set in Eqs. 4i and 4j. Demand y_t is implicitly bounded by the function g.

$$
\begin{aligned}
\min \quad & \sum_{t \in \mathcal{T}} \sum_{u \in \mathcal{U}} C_{u,t} q_{u,t} && && \text{(4a)} \\
\text{s.t.} \quad & \underline{q}_{u,t} \leq q_{u,t} \leq \overline{q}_{u,t} && \forall t \in \mathcal{T}, u \in \mathcal{U} && \text{(4b)} \\
& \sum_{u \in \mathcal{U}} q_{u,t} = y_t && \forall t \in \mathcal{T} && \text{(4c)} \\
& \sigma_t = \sigma_{t-1} + \sigma_t^+ + \lambda_t && \forall t \in \mathcal{T} \setminus \{1\} && \text{(4d)} \\
& \sigma_t = \sigma^0 + \sigma_t^+ && t = 1 && \text{(4e)} \\
& \sigma_t \leq \overline{\sigma} && \forall t \in \mathcal{T} && \text{(4f)} \\
& x_t = f(B_t, x_{t-1}, u_t) && \forall t \in \mathcal{T} && \text{(4g)} \\
& y_t = g(B_t, x_t, u_t) && \forall t \in \mathcal{T} && \text{(4h)} \\
& 0 \leq x_t \leq 1 && \forall t \in \mathcal{T} && \text{(4i)} \\
& -1 \leq u_t \leq 1 && \forall t \in \mathcal{T} && \text{(4j)} \\
& \frac{1}{|\mathcal{T}|} \sum_{t \in \mathcal{T}} u_t^{\mathrm{ABS}} \leq \Delta && && \text{(4k)} \\
& -u_t \leq u_t^{\mathrm{ABS}} \leq u_t && \forall t \in \mathcal{T} && \text{(4l)}
\end{aligned}
$$

Assume that the functions f and g capture the evolution of the state x_t and that higher or lower price signals u_t are necessary depending on the value of the state, but that they do not restrict the price signal u_t (This is the case for the demand response model applied in this study.). Then, the solution to the problem in Eqs. 4a to 4j corresponds to a direct control problem, because the unrestricted indirect control variable u_t would be set such that it corresponds to directly controlling y_t and x_t.

However, the motivation for modelling demand response as an indirect control problem is that issuing the price signal u_t is associated with societal costs. Without incentive, consumers are unwilling to change their demand y_t.

Equations 4k and 4l express the desire to retain societal costs for demand response: We start from the (normalised) expression $|u_t(y_t - B_t)|$, which would be equivalent to the (normalised) costs caused by demand response. If positive, the expression inside the absolute value corresponds to the additional cost incurred by consumers in time step t as a result of their response; if negative, it is equivalent to the losses society suffers from reduced consumer payments. In order to avoid this quadratic expression in the objective function, we instead force the average absolute value of u_t across time steps to be lower than a threshold Δ. The sensitivity of our results towards that parameter is discussed in Section 4.

Note, that in Eq. 4, we write demand y and state x in lower case letters to denote variables in discrete time, in contrast to Eqs. 1 and 2, where capital letters denote variables in continuous time.

The transition from Eq. 3 to Eq. 4 introduces two key challenges: Firstly, Eq. 4g and especially Eq. 4h can be non-linear. This constitutes increased problem complexity in comparison to Eq. 3. Secondly, even if existing modelling frameworks could handle the above non-linearity, it would require reformulating their energy balance equations. Modifying the code of established modelling frameworks poses practical challenges, which is a hurdle to adaptation of the above formulation.

(Piece-wise) linearisation of Demand Response. In this study, the function f is assumed linear and deterministic (Eq. 1). Further, it is assumed discrete in time at the same temporal resolution as the dispatch problem. Hence, it can be formulated as Eq. 5:

$$f(B_t, x_{t-1}, u_t) = \frac{1}{C}(y_t - B_t), \tag{5}$$

where y_t and x_{t-1} are written in lower letters to indicate decision variables.

The post-response demand y_t is given by function g and is non-linear [29]. Hence, it is approximated via a piece-wise linear model (Eq. 6):

$$g(B_t, x_t, u_t) \approx \sum_{\substack{\{i\in\mathcal{I}:\\ \underline{B}_i\le B_t\le\overline{B}_i,\\ \underline{u}_i\le u_t\le\overline{u}_i,\\ \underline{X}_i\le x_{t-1}\le\overline{X}_i\}}} \beta_i^0 + \beta_i^{\mathrm{B}} B_t + \beta_i^{\mathrm{u}} u_t + \beta_i^{\mathrm{X}} x_{t-1} \tag{6}$$

There, $i \in \mathcal{I}$ denote the set of segments of the piece-wise linear function, where a segment i is activated if all variables are within their respective interval in that segment, i.e if $\underline{B}_i \le B_t \le \overline{B}_i$ and $\underline{u}_i \le u_t \le \overline{u}_i$ and $\underline{X}_i \le x_t \le \overline{X}_i$. β_i^0 is the intercept in segment i, and β_i^{B} ($\beta_i^{\mathrm{u}}, \beta_i^{\mathrm{X}}$) are the coefficients for B_t (u_t, x_t). In this study, we estimate this function as a linear tree using the implementation of [45]. The authors make the analogy of a regression tree. In each leaf node, a linear regression is fitted which corresponds to a piece-wise linear function. This method does not require a pre-determined segmentation. The piece-wise linear approximation of g and keeping f linear allows us to approximate the problem in Eq. 7 as a mixed-integer linear program.

Integration of multiple energy carriers and final model. In this study, we analyse the role of demand response from electrified heating demand as well as heat storage in the Danish electricity dispatch. This aspect together with the piece-wise linear approximation described in the previous section, are formulated in Eq. 7.

Hence, both energy carriers, electricity and heat, need to be modelled. We denote inflexible electricity demand by D_t and flexible electrified heating demand by y_t (Eq. 7c). Conversion from electricity to heat is allowed at a fixed rate ϕ. To ensure dispatch feasibility, electricity and heat slack generation δ_t^{el} and δ_t^{h} is permitted at penalty costs P^{el} and P^{h}.

Furthermore, heat storage is added to the model as an investment option at annualised investment costs C^{INV} (Eq. 7a). Electricity storage capacity is assumed fixed. Storage of electricity is indicated by superscript "el" and storage of heat by superscript "h" (Eqs. 7d to 7h).

Heat demand response is modelled by the following equations: The state function (Eq. 1) is already linear and formulated explicitly in Eq. 7l. The piece-wise approximation of the function g is formulated in Eq. 7m, whereas the respective pieces are set by Eqs. 7n to 7p and bound by Eqs. 7q to 7s. Equations 7t and 7u ensure that only one piece is active. Electrified heat generation is further bound by the installed (heat) capacity of electric boilers and heat pumps $\overline{y}$ (Eq. 7j).

$$\begin{aligned}
\min \quad & \sum_{t\in\mathcal{T}}\sum_{u\in\mathcal{U}} C_{u,t} q_{u,t} \\
& + C^{\mathrm{INV}}\overline{\sigma}^{\mathrm{h}} + \sum_{t\in\mathcal{T}}(P^{\mathrm{el}}\delta_t^{\mathrm{el}} + P^{\mathrm{h}}\delta_t^{\mathrm{h}}) && && \text{(7a)}\\
\text{s.t.} \quad & 0 \le q_{u,t} \le \overline{q}_{u,t} && \forall t\in\mathcal{T}, u\in\mathcal{U} && \text{(7b)}\\
& \sum_{u\in\mathcal{U}} q_{u,t} + \sigma_t^{\mathrm{el+}} + \sigma_t^{\mathrm{h+}} + \delta_t^{\mathrm{el}} = D_t + \phi^{-1} y_t && \forall t\in\mathcal{T} && \text{(7c)}\\
& \sigma_t^{\mathrm{el}} = \sigma_{t-1}^{\mathrm{el}} + \sigma_t^{\mathrm{el+}} && \forall t\in\mathcal{T}\setminus\{1\} && \text{(7d)}\\
& \sigma_t^{\mathrm{el}} = \sigma^{\mathrm{el0}} + \sigma_t^{\mathrm{el+}} && t = 1 && \text{(7e)}\\
& \sigma_t^{\mathrm{el}} \le \overline{\sigma}^{\mathrm{el}} && \forall t\in\mathcal{T} && \text{(7f)}\\
& \sigma_t^{\mathrm{h}} = \sigma_{t-1}^{\mathrm{h}} + \sigma_t^{\mathrm{h+}} && \forall t\in\mathcal{T}\setminus\{1\} && \text{(7g)}\\
& \sigma_t^{\mathrm{h}} = \sigma^{\mathrm{h0}} + \sigma_t^{\mathrm{h+}} && t = 1 && \text{(7h)}\\
& \sigma_t^{\mathrm{h}} \le \overline{\sigma}^{\mathrm{h}} && \forall t\in\mathcal{T} && \text{(7i)}\\
& y_t + \sigma_t^{\mathrm{h+}} \le \overline{y} + \delta_t^{\mathrm{h}} && \forall t\in\mathcal{T} && \text{(7j)}\\
& -y_t \le \sigma_t^{\mathrm{h+}} \le \overline{y} && \forall t\in\mathcal{T} && \text{(7k)}\\
& x_t = x_{t-1} + \frac{1}{C}(y_t - B_t) && \forall t\in\mathcal{T} && \text{(7l)}\\
& y_t = \sum_{i\in\mathcal{I}} \alpha_{i,t}\beta_i^0 + \beta_i^{\mathrm{B}}\tilde{B}_{i,t} + \beta_i^{\mathrm{u}}\tilde{u}_{i,t} + \beta_i^{\mathrm{X}}\tilde{x}_{i,t} && \forall t\in\mathcal{T} && \text{(7m)}
\end{aligned}$$

$$B_t = \sum_{i\in\mathcal{I}} \tilde{B}_{i,t} \qquad \forall t \in \mathcal{T} \quad (7n)$$

$$u_t = \sum_{i\in\mathcal{I}} \tilde{u}_{i,t} \qquad \forall t \in \mathcal{T} \quad (7o)$$

$$x_t = \sum_{i\in\mathcal{I}} \tilde{x}_{i,t} \qquad \forall t \in \mathcal{T} \quad (7p)$$

$$\underline{B}_i\alpha_{i,t} \leq \tilde{B}_{i,t} \leq \overline{B}_i\alpha_{i,t} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \quad (7q)$$

$$\underline{u}_i\alpha_{i,t} \leq \tilde{u}_{i,t} \leq \overline{B}_i\alpha_{i,t} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \quad (7r)$$

$$\underline{X}_i\alpha_{i,t} \leq \tilde{x}_{i,t} \leq \overline{X}_i\alpha_{i,t} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \quad (7s)$$

$$\sum_{i\in\mathcal{I}} \alpha_{i,t} = 1 \qquad \forall t \in \mathcal{T} \quad (7t)$$

$$\alpha_{i,t} \in \{0, 1\} \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \quad (7u)$$

$$0 \leq x_t \leq 1 \qquad \forall t \in \mathcal{T} \quad (7v)$$

$$-1 \leq u_t \leq 1 \qquad \forall t \in \mathcal{T} \quad (7w)$$

$$0 \leq \tilde{B}_{i,t} \leq 1 \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \quad (7x)$$

$$0 \leq \tilde{x}_{i,t} \leq 1 \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \quad (7y)$$

$$-1 \leq \tilde{u}_{i,t} \leq 1 \qquad \forall i \in \mathcal{I}, t \in \mathcal{T} \quad (7z)$$

$$\frac{1}{|\mathcal{T}|} \sum_{t\in\mathcal{T}} u_t^{\text{ABS}} \leq \Delta \quad (7aa)$$

$$-u_t \leq u_t^{\text{ABS}} \leq u_t \qquad \forall t \in \mathcal{T} \quad (7ab)$$

4. Case study

This section outlines our case study setup, including a description of the scenarios investigated (see Section 4.1). Results are discussed in Section 4.2.

4.1. Case study description

This study applies the modelling setup described in Section 3 to analyse the impact of electrified heat demand flexibility (cost-optimally sized heat storage and demand response) in the Danish power dispatch of 2050. We investigate a range of system configurations defined in Section 4.1.1. As demand response, we consider the flexibility offered by the thermal mass of piping water in the Danish district heating system and building envelopes of dwellings. We present this, alongside other input data, in more detail in Section 4.1.2. An overview on our computational setup is given in Section 4.1.3.

4.1.1. Scenario definition

We analyse different degrees of heat demand flexibility across 10 scenarios, defined in Table 1: A reference plan4EU run without consideration of heat demand flexibility serves as a `Ref` scenario (Section 3.1). The `DR`, `HS` and `DR+HS` scenarios are run to analyse different degrees of heat demand flexibility, indicating the addition of power-to-heat demand response, heat storage and both, respectively. Under the same demand flexibility sources, the `DR|-10%ES`, `HS|-10%ES` and `DR+HS|-10%ES` scenarios reduce Danish electricity storage capacity by 10% to investigate whether heat demand flexibility might allow for a reduction in electricity storage capacity. Here, the `Ref.|-10%ES` scenario is introduced as a reference case with the same electricity storage reduction. Finally, the sensitivity of our results toward variations in the maximum average absolute price signal Δ (see Section 3.4) is analysed in scenarios `DR|pr.=0.1` and `DR|pr.=0.03`.

Table 1: Scenario definition. The abbreviations *DR*, *HS* and *ES* refer to *demand response*, *heat storage* and *electricity storage* respectively. The parameter Δ sets an upper bound on the average absolute value of the penalty signal u, normalised between -1 and 1 (see Section 3.4).

Scenario	DR	Heat st.	El. st.	Δ
`Ref`	-	-	100%	-
`DR`	x	-	100%	0.05
`HS`	-	x	100%	-
`DR+HS`	x	x	100%	0.05
`Ref.|-10%ES`	-	-	90%	-
`DR|-10%ES`	x	-	90%	0.05
`HS|-10%ES`	-	x	90%	-
`DR+HS|-10%ES`	x	x	90%	0.05
`DR|pr.=0.1`	-	-	100%	0.1
`DR|pr.=0.03`	-	-	100%	0.03

4.1.2. Input data

Electricity generation capacities and aggregated yearly demand. The installed electricity generation portfolio corresponds to the pathway results of the Techno-Friendly scenario of the openENTRANCE project [46]. The scenarios and top-level results are openly available in the openENTRANCE scenario explorer [47]. The data relevant for the Danish system is given in Table 2. Electricity imports and exports are priced at the marginal generation costs of the respective interconnected country.

Table 2: Installed capacities (Denmark). Source: [46]. *Disregarded in Frigg as insignificant.

	Capacity [GW]	Var. costs (incl. fuel costs) [EUR/MWh]
Electricity generators		
Biomass (with CCS)	3.02	42.79
Biomass (without CCS)	0.62	38.30
Hard coal (without CCS)	0.02	4.03
Natural Gas (CCGT with CCS)	0.25	54.14
Hydro*	0.01	0.00
Solar	8.00	0.00
Wind (Offshore)	13.79	0.00
Wind (Onshore)	5.79	0.00
Interconnections		
Germany	3.1	Variable
Benelux	0.7	Variable
UK	1.4	Variable
Norway	1.7	Variable
Sweden	2.4	Variable

Time series data. We apply hourly load factors for VRES and demand per electricity sub-sector from the Plan4Res project [48]. Hourly marginal generation cost of Denmark's neighbour countries in the `Ref` run serve as both import and export prices. All time series data are openly available and applied here for 37 climatic years. All analyses use these climatic years to improve robustness, and mean values across climatic years are presented as results. The data are available at [48].

Flexibility Function parameters. With the exception of demand response capacity C, all parameters of the Flexibility Function (see Section 3.3), are chosen as in [12] and discussed in more depth in [27]. The parameter C indicates the maximum amount of energy that can be "stored" in demand response. Similarly to [12], we consider this value to comprise the sum of the thermal inertia of district heating piping water and residential building envelopes in Denmark. For the latter, we apply the same per-unit value as in [12], namely 1.16, assuming maximum temperature variations of the building envelopes of ± 1K. The piping water's thermal inertia is computed as the product of its volume, 1 bn. liters [49], assuming the same value as today, a density of 0.997 kg/l, a thermal capacity of 4200 kg/K and maximum temperature variations of 7K (±3.5K). The resulting value is scaled by the maximum demand in the respective climatic year of plan4EU.

Power-to-heat capacity. In Frigg, power-to-heat capacity, parameter $\bar{y}$ in Eq. 7 is set to 120% of the maximum power-to-heat load in the plan4EU `Ref.` scenario. This corresponds to 37.695 GW-heat.

4.1.3. Implementation

plan4EU is implemented in the SMS++ framework [50]. Frigg is implemented in Python 3.9.11 [51]. The Flexibility Function approximation is estimated with the linear-tree package [45], all optimisation programs are implemented in PuLP [52] and solved with Gurobi 9.5.1 [53] and CBC [54].

4.2. Results & discussion

Results are described and discussed in the following, starting with parameter tuning of the piece-wise linear demand response approximation in Section 4.2.1. This is followed by an analysis of the Danish electricity system across the scenarios described above in Sections 4.2.2 and 4.3.

4.2.1. Approximator tuning

Prior to the main runs, the results of which are described in the section Section 4.2.2, we conducted Frigg-only runs in the `DR` scenario to determine the number of segments in the piece-wise linear approximation based on five, out of 37, climatic years. The results of this analysis are given in Table 3. The first column indicates the maximum number of segments the approximation could result in [1].

A maximum run time of 72 hours was set, such that, under some configurations, setting the maximum number of segments higher than 12 resulted in not all runs terminating successfully within that time. Average and maximum run times seem to increase with a higher number of segments, although there are some exceptions, especially for configurations with some runs not terminating successfully. However, approximation accuracy improves with a higher number of segments, as indicated by lower mean absolute error (MAE) values.

Two MAE metrics have been calculated: MAE (train) refers to the error in estimating the model, which was done on 20,000 training data points for x_t, u_t and B_t uniformly distributed within their bounds. MAE (appr.) indicates the error made by the piece-wise linear approximation within the MILP model compared to simulating demand based on the price signals determined by the MILP. Surprisingly, the approximation is not always more accurate in training than when applied in the optimisation model (MAE (appr.)), which might be due to the optimisation model choosing to keep the demand at lower levels compared to the uniformly distributed training data.

The last two columns in Table 3 show savings in comparison to the `Ref` scenario. Approximated savings indicate those in the mixed-integer linear program (MILP). Here, "Savings (appr.)" indicate the difference between the `Ref` scenario and the optimal objective value of the MILP using the piece-wise linear approximation. For "Savings (sim.)", demand response to optimal penalty signals, as determined by the optimisation model is simulated. Then, the optimisation is solved again with demand fixed to these values. Here, savings increase with a higher number of piece-wise linear segments and, as expected, approximated savings are smaller than simulated savings. We considered simulated savings as the main indicator of solution quality and, based on that, the maximum number of segments was set to 8 as yielding a reasonable trade-off between runtime and accuracy.

4.2.2. Impact of Danish power-to-heat demand response

In the following sub-section, the analysis of the power-to-heat demand flexibility in the form of demand response (`DR` scenario), heat storage (`HS`) and both (`DR+HS`) is compared to a reference case (`Ref`).

Electricity mix. In the `Ref` scenario, the 2050 EU electricity mix is carbon-neutral with biomass and natural gas-fired electricity generation featuring carbon capture (Appendix D). Wind power is the main source of electricity covering 38% of electricity demand, followed by solar and hydro power, whereas nuclear power is the largest source of conventional power generation.

Danish 2050 electricity generation is heavily dominated by wind power, supplying 91% of the total generation in the `Ref` scenario. The majority of the remaining load is covered by solar power at 8 % (Table 4).

The sole introduction of power-to-heat demand response seems to have no significant influence on either the Danish or EU electricity mix, where no changes are observable. The addition of heat storage allows the uptake of an additional 0.68 TWh of wind, water and solar electricity in the Danish system (ca. 1% of total annual electricity load) and 2.1 TWh on an EU level (0.4% of annual electricity load). Results under the `DR+HS`

[1] The linear-tree package [45] estimates piece-wise linear models as regression trees with linear models in the leave nodes and only allows setting the minimum fraction of observations per leave node.

Table 3: Approximator performance in five climatic years. MAE stands for mean absolute error. "train" indicates performance on training data during model estimation, "appr." denotes performance when applying the approximation in the MILP and "sim." indicates performance when re-running the problem as an linear program (LP). Savings refer to the difference in objective value compared to a baseline run. MAE and savings are average values across climatic years.

Max. no. segments	Successful runs [%]	Avg. run time [h]	Max. run time [h]	MAE (train)	MAE (appr.)	Savings (appr.) [%]	Savings (sim.) [%]
4	100	4.4	7.2	0.094	0.046	3.04	1.85
6	100	9.7	13.1	0.073	0.047	3.09	2.06
8	100	13.7	22.0	0.056	0.046	3.11	2.17
10	100	13.7	20.9	0.050	0.046	3.10	2.19
12	100	38.9	54.7	0.040	0.054	3.12	2.02
14	80	50.0	60.6	0.038	0.045	3.22	2.42
16	60	36.1	48.0	0.034	0.034	2.96	2.48
18	40	42.4	52.3	0.029	0.034	2.58	2.34

scenario indicate no significant difference in electricity mix to the `HS` scenario.

Danish cross-border trade. In the `Ref` scenario, electricity imports to the Danish system amount to 29.07 TWh in total, with Sweden being the largest source followed by Germany, Norway, the UK and The Netherlands (Appendix A). Denmark is a net exporter of electricity, with aggregated `Ref` electricity exports exceeding imports at 45.54 TWh with Germany making the largest contribution followed by the UK (Appendix B).

Under the `DR` scenario, these numbers remain fairly constant, with slight shifts in the distributions of imports and exports. The addition of heat storage seems to lower total imports and increase exports. At the same time, imports from and exports to Norway are growing by ca. 0.3 TWh, and the opposite effect can be observed for Denmark's other neighbours. Again, the `DR+HS` scenario shows similar system operation as the `HS` scenario.

System cost. Already in the `Ref` scenario, OPEX are dominated by imports and exports rather than domestic dispatch cost (Table 5). Export revenues of EUR 826.88 mill. exceed import costs and domestic dispatch costs by far, contributing to total OPEX of -20.25 EUR/MWh. Notably, import costs and export revenues are no explicit part of plan4EU, which solves one dispatch problem for the entire European system modelled. Rather, they are computed a-posteriori as the product of import/export quantities and marginal generation costs in the respective neighbour of the Danish system. Frigg applies that approach for demand flexibility optimisation.

The introduction of demand response slightly lowers system cost by ca. 2%, mainly by increasing export revenues. A more significant change can be seen in the `HS` scenario, where import costs decrease by 17% and export revenues grow by 6% in comparison to the `Ref` scenario leading to a ca. 6% reduction in overall system cost. This is achieved through the investment in 388 GWh heat storage (Appendix C), which corresponds to 10.3 hours of power-to-heat peak load. OPEX do not seem to change significantly in the `DR+HS` scenario. However, annualised investment costs are reduced by ca. EUR 4.4 mill. in comparison to the `HS` scenario.

4.3. Sensitivity analysis

Sensitivity of the study results described above with respect to a 10% reduction in Danish electricity storage (`Ref.|-10%ES` , `DR|-10%ES` , `HS|-10%ES` , `DR+HS|-10%ES`) and a modification in price sensitivity (parameter Δ) from $\Delta = 0.05$ to $\Delta = 0.1$ (`DR|pr.=0.1`) and $\Delta = 0.03$ (`DR|pr.=0.03`) is outlined in the following.

Electricity storage capacity reduction. The `Ref.|-10%ES` scenario does not feature power-to-heat demand flexibility, but a 10% reduction in Danish electricity storage capacity. This reduction seems to mildly impact system cost at an overall increase of 0.3% in comparison to the `Ref` scenario (Table 5). Introducing power-to-heat demand response under this reduction leads to cost savings of 0.5% in comparison to the `Ref.|-10%ES` scenario, which is lower than the relative savings at default electricity storage capacity. Both the `HS|-10%ES` and `DR+HS|-10%ES` yield higher OPEX than if electricity storage is not decreased. However, heat storage (Appendix C capacities do not differ. One explanation could be that power-to-heat capacity is a limiting factor to exploiting further power-to-heat flexibility.

Modified demand response welfare bounds. We impose an upper bound Δ on the average absolute price signal u_t (c.f. Section 3.4). This bound expresses the desire to retain neutral penalty signals and low welfare losses through demand response. Imposing no bound at all would lead to the same solution as under direct control of demand response, since the model would choose penalty signals that correspond to optimal direct control.

In the `DR` scenario, we set this bound to $\Delta = 0.05$ and vary it to $\Delta = 0.03$ and $\Delta = 0.1$ in the `DR|pr.=0.03` and `DR|pr.=0.1` scenario respectively. A tighter bound leads to cost savings of 1.73%, which are 24% lower than in the `DR` scenario (Table 5). Increasing the bounds to $\Delta = 0.1$ gives slightly larger savings of 2.2%, an increase of 12% in comparison to the `DR` scenario. While the differences across these three scenarios are mild, at least for the variations tested here, the cost savings potential of demand response seems to be sensitive to this bound.

5. Conclusion

In this study, a major update of Frigg, a soft-linking framework for integrating direct and indirect demand flexibility into

Table 4: Danish electricity mix in plan4EU in TWh (relative difference to `Ref` scenario). Dark red (blue) colours indicate high absolute growth (reduction) with respect to the `Ref` scenario.

	`Ref`	`DR`	`HS`	`DR+HS`	`Ref.|-10%ES`	`DR|-10%ES`	`HS|-10%ES`	`DR+HS|-10%ES`	`DR|pr.=0.03`	`DR|pr.=0.1`
Hydro	0.05 (±0.0%)	0.05 (+0.07%)	0.05 (+0.73%)	0.05 (+0.73%)	0.05 (-0.13%)	0.05 (+0.04%)	0.05 (+0.72%)	0.05 (+0.72%)	0.05 (+0.07%)	0.05 (+0.15%)
Coal	0.05 (±0.0%)	0.05 (+1.55%)	0.05 (-1.73%)	0.05 (-1.24%)	0.05 (+0.03%)	0.05 (+0.17%)	0.05 (-2.49%)	0.05 (-2.49%)	0.05 (+1.0%)	0.05 (+0.64%)
Wind	59.5 (±0.0%)	59.51 (+0.03%)	60.02 (+0.88%)	59.98 (+0.82%)	59.45 (-0.07%)	59.52 (+0.04%)	59.99 (+0.83%)	59.99 (+0.83%)	59.5 (+0.01%)	59.55 (+0.1%)
Solar	5.39 (±0.0%)	5.39 (+0.13%)	5.54 (+2.8%)	5.54 (+2.84%)	5.38 (-0.14%)	5.41 (+0.41%)	5.53 (+2.71%)	5.53 (+2.71%)	5.39 (+0.14%)	5.43 (+0.78%)
Biomass	0.11 (±0.0%)	0.11 (-3.03%)	0.06 (-45.54%)	0.06 (-45.3%)	0.11 (+1.36%)	0.11 (-0.25%)	0.06 (-45.37%)	0.06 (-45.37%)	0.11 (-0.97%)	0.1 (-6.23%)
Natural gas	0.01 (±0.0%)	0.01 (-8.24%)	0.01 (-52.72%)	0.01 (-50.96%)	0.01 (+2.18%)	0.01 (-5.75%)	0.0 (-60.31%)	0.0 (-60.31%)	0.01 (-4.83%)	0.01 (-14.43%)
Total	65.1 (±0.0%)	65.12 (+0.03%)	65.72 (+0.95%)	65.69 (+0.9%)	65.05 (-0.07%)	65.15 (+0.07%)	65.69 (+0.9%)	65.69 (+0.9%)	65.11 (+0.02%)	65.19 (+0.14%)

Table 5: Costs in the Danish electricity system (relative difference to `Ref` scenario). Quantities and dispatch cost are plan4EU output. Import costs and export revenues have been post-calculated, pricing both at marginal production cost in the respective system connected to the Danish system. Dark red (blue) colours indicate high absolute growth (reduction) with respect to the `Ref` scenario.

	`Ref`	`DR`	`HS`	`DR+HS`	`Ref.|-10%ES`	`DR|-10%ES`	`HS|-10%ES`	`DR+HS|-10%ES`	`DR|pr.=0.03`	`DR|pr.=0.1`
Domestic generation costs [M EUR]	5.56 (±0.0%)	5.37 (-3.44%)	3.07 (-44.7%)	3.1 (-44.26%)	5.64 (+1.41%)	5.51 (-0.87%)	3.03 (-45.48%)	3.03 (-45.48%)	5.48 (-1.32%)	5.17 (-6.91%)
Import costs [M EUR]	256.67 (±0.0%)	252.87 (-1.48%)	213.27 (-16.91%)	212.55 (-17.19%)	256.37 (-0.12%)	255.79 (-0.34%)	215.77 (-15.93%)	215.77 (-15.93%)	253.36 (-1.29%)	252.17 (-1.75%)
Export revenues [M EUR]	826.88 (±0.0%)	833.98 (+0.86%)	873.28 (+5.61%)	873.76 (+5.67%)	825.21 (-0.2%)	827.52 (+0.08%)	867.2 (+4.88%)	867.2 (+4.88%)	833.28 (+0.77%)	834.44 (+0.91%)
Heat storge investment cost [M EUR]	0.0 (-)	0.0 (-)	58.78 (-)	54.0 (-)	0.0 (-)	0.0 (-)	58.78 (-)	54.07 (-)	0.0 (-)	0.0 (-)
Total [M EUR]	-564.65 (±0.0%)	-575.75 (-1.96%)	-598.15 (-5.93%)	-604.11 (-6.99%)	-563.2 (+0.26%)	-566.22 (-0.28%)	-589.62 (-4.42%)	-594.34 (-5.26%)	-574.43 (-1.73%)	-577.1 (-2.2%)
Total [EUR/MWh]	-20.25 (±0.0%)	-20.64 (-1.96%)	-21.45 (-5.93%)	-21.66 (-6.99%)	-20.19 (+0.26%)	-20.3 (-0.28%)	-21.14 (-4.42%)	-21.31 (-5.26%)	-20.6 (-1.73%)	-20.69 (-2.2%)

large-scale energy system modelling has been proposed. The framework specifically addresses the integration of indirect, non-linear demand response models and extends previous work in [12]. It is based on a piece-wise linear approximation of said demand response model in a mixed-integer linear program which optimises demand flexibility. The present update addresses central shortcomings of the approach proposed in [12] by allowing the representation of an arbitrary number of intertemporal constraints and of welfare losses through demand response.

The framework is applied to link plan4EU, an electricity dispatch model of large parts of Europe, with a Flexibility Function [29] to analyse the role of Danish power-to-heat demand flexibility in the Danish and European electricity systems under 37 climatic years. This flexibility comprises end-user demand response and optimally sized heat storage.

Results. We find that both demand response and heat storage reduce Danish system costs by ca. 2% and 6% respectively, mainly by leveraging the Danish position as an electricity transit country to achieve lower import costs and higher export revenues in comparison to a reference case. Cost savings from heat storage exceed those from demand response and their combination leads to similar operational savings, while reducing heat storage investments in comparison to a case without demand response.

An analysis of electricity storage capacity reduction in relation to power-to-heat demand flexibility remains inconclusive, as the effect of power-to-heat demand flexibility with that reduction falls short of its effect under non-reduced electricity storage.

Our results suggest that the cost-savings potential of demand response is sensitive to variations of the acceptable welfare loss through demand response. We approximate this welfare loss through an upper bound on the average absolute price signal. Imposing no such bound corresponds to direct control of demand response, which would likely lead to higher savings. Thus, these results indicate that modelling demand response as an indirect rather than a direct control problem does in fact lead to different numerical results.

A preliminary methodological analysis on five climatic years of the piece-wise linear demand response model approximation suggests a segmentation into eight pieces as a reasonable trade-off between approximation performance and run time, where the savings of ca. 2.2% are achieved at an average runtime of 13.7 hours and an approximation error of 4.6%.

Limitations and future research. This study contributes both a methodological novelty, in integrating indirect demand response into large-scale energy system modelling, and an analytical novelty, in applying that method to a case study on Danish power-to-heat demand flexibility.

With electricity imports and exports being the main contributors to savings made by demand flexibility, numerical results might be sensitive towards the approach of calculating import costs and export revenues. Here, both have been priced at the marginal generation costs in the respective neighbour country.

While a high temporal resolution, one hour in electricity dispatch modelling and 3.6 seconds in demand response simulation, has been applied, the Danish electricity and heat sector is modelled as a single-node system. Also, district and individual heating have not been represented separately. A more detailed representation of the Danish electricity and heat sector could be one line of future research.

While the Flexibility Function can be estimated from data, it is partially assumption-based in this study. Further research could model demand response characteristics in higher detail and estimate model parameters from observed data.

Finally, future work could refine the representation of welfare loss through demand response. We express this by setting an upper bound on the average absolute price signal. Yet, ideally, the societal cost of demand response could be monetised in a more direct way.

CRediT authorship contribution statement

Amos Schledorn: Conceptualization, Methodology, Software, Data curation, Investigation, Formal analysis, Visualization, Writing - original draft. **Sandrine Charousset:** Conceptualization, Methodology, Software, Data curation, Writing - original draft. **Rune Grønborg Junker:** Conceptualization, Methodology, Writing - review & editing. **Daniela Guericke:** Methodology, Writing - review & editing, Supervision. **Henrik Madsen:** Writing - review & editing, Supervision. **Dominik Franjo Dominković:** Conceptualization, Methodology, Writing - review & editing, Supervision.

Declaration of competing interests

The authors declare that they have no known competing interests that could have influenced the work reported in this paper.

Acknowledgements

This work is financed through the projects openEntrance and Elexia. OpenEntrance has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 835896. Elexia is a Horizon Europe funded project under grant agreement ID: 101075656. We would also like to acknowledge funding from the EUDP-funded project Digitalization of district heating, case number: 64019-0545. The authors would like to thank Simon Scott Palmer from GlobalDenmark A/S for proofreading.

References

[1] European Commission, 'Fit for 55': delivering the EU's 2030 Climate Target on the way to climate neutrality, Tech. rep., Brussels (7 2021). URL https://ec.europa.eu/clima/citizens/support_en.

[2] B. Pickering, F. Lombardi, S. Pfenninger, Diversity of options to eliminate fossil fuels and reach carbon neutrality across the entire European energy system, Joule 6 (6) (2022) 1253–1276. doi:10.1016/j.joule.2022.05.009.

[3] T. Brown, D. Schlachtberger, A. Kies, S. Schramm, M. Greiner, Synergies of sector coupling and transmission reinforcement in a cost-optimised, highly renewable European energy system, Energy 160 (2018) 720–739. doi:10.1016/j.energy.2018.06.222.

[4] T. H. Ruggles, J. A. Dowling, N. S. Lewis, K. Caldeira, Opportunities for flexible electricity loads such as hydrogen production from curtailed generation, Advances in Applied Energy 3 (8 2021). doi:10.1016/j.adapen.2021.100051.

[5] Folketinget, Lov om klima (2020).

[6] Danish Energy Agency, Denmark's Climate and Energy Outlook 2020, Tech. rep. (2020). URL https://ens.dk/sites/ens.dk/files/Basisfremskrivning/deco_2020_27082020.pdf

[7] H. Lund, J. Z. Thellufsen, P. Sorknæs, B. V. Mathiesen, M. Chang, P. T. Madsen, M. S. Kany, I. R. Skov, Smart energy Denmark. A consistent and detailed strategy for a fully decarbonized society, Renewable and Sustainable Energy Reviews 168 (10 2022). doi:10.1016/j.rser.2022.112777.

[8] W. Heitkoetter, B. U. Schyska, D. Schmidt, W. Medjroubi, T. Vogt, C. Agert, Assessment of the regionalised demand response potential in Germany using an open source tool and dataset, Advances in Applied Energy 1 (2 2021). doi:10.1016/j.adapen.2020.100001.

[9] Danish Energy Agency, Regulation and planning of district heating in Denmark, Tech. rep. (2017). URL http://www.ens.dk/sites/ens.dk/files/climate-co2/Global-Cooperation/Publications/Publications/regulation_and_planning_of_district_heating_in_denmark.pdf

[10] D. F. Dominkovic, Modelling Energy Supply of Future Smart Cities, Ph.D. thesis, Technical University of Denmark (2018). URL https://backend.orbit.dtu.dk/ws/portalfiles/portal/153690178/Thesis_merged_12072018.pdf

[11] K. Hedegaard, M. Münster, Influence of individual heat pumps on wind power integration - Energy system investments and operation, Energy Conversion and Management 75 (2013) 673–684. doi:10.1016/j.enconman.2013.08.015.

[12] A. Schledorn, G. R. Junker, D. Guericke, H. Madsen, D. F. Dominković, Frigg: Soft-Linking Energy System and Demand Response Models, Applied Energy 317 (2022). doi:https://doi.org/10.1016/j.apenergy.2022.119074.

[13] S. Pfenninger, A. Hawkes, J. Keirstead, Energy systems modeling for twenty-first century energy challenges, Renewable and Sustainable Energy Reviews 33 (2014) 74–86. doi:10.1016/j.rser.2014.02.003. URL http://dx.doi.org/10.1016/j.rser.2014.02.003

[14] M. Chang, J. Z. Thellufsen, B. Zakeri, B. Pickering, S. Pfenninger, H. Lund, P. A. Østergaard, Trends in tools and approaches for modelling the energy transition, Applied Energy 290 (2021). doi:10.1016/j.apenergy.2021.116731.

[15] V. Z. Gjorgievski, N. Markovska, A. Abazi, N. Duić, The potential of power-to-heat demand response to improve the flexibility of the energy system: An empirical review, Renewable and Sustainable Energy Reviews 138 (3 2021). doi:10.1016/j.rser.2020.110489.

[16] F. Frischmuth, P. Härtel, Hydrogen sourcing strategies and cross-sectoral flexibility trade-offs in net-neutral energy scenarios for Europe, Energy 238 (1 2022). doi:10.1016/j.energy.2021.121598.

[17] M. Chang, H. Lund, J. Z. Thellufsen, P. A. Østergaard, Perspectives on purpose-driven coupling of energy system models, Energy 265 (2023)

126335. doi:10.1016/j.energy.2022.126335.
URL https://linkinghub.elsevier.com/retrieve/pii/S0360544222032212

[18] K. S. Andersen, L. B. Termansen, M. Gargiulo, B. P. Ó Gallachóirc, Bridging the gap using energy services: Demonstrating a novel framework for soft linking top-down and bottom-up models, Energy 169 (2019) 277–293. doi:10.1016/j.energy.2018.11.153.

[19] M. Brinkerink, B. Zakeri, D. Huppmann, J. Glynn, B. Ó Gallachóir, P. Deane, Assessing global climate change mitigation scenarios from a power system perspective using a novel multi-model framework, Environmental Modelling and Software 150 (4 2022). doi:10.1016/j.envsoft.2022.105336.

[20] H. Blanco, J. J. Gómez Vilchez, W. Nijs, C. Thiel, A. Faaij, Soft-linking of a behavioral model for transport with energy system cost optimization applied to hydrogen in EU, Renewable and Sustainable Energy Reviews 115 (January) (2019) 109349. doi:10.1016/j.rser.2019.109349.
URL https://doi.org/10.1016/j.rser.2019.109349

[21] M. Aunedi, M. Yliruka, S. Dehghan, A. M. Pantaleo, N. Shah, G. Strbac, Multi-model assessment of heat decarbonisation options in the UK using electricity and hydrogen, Renewable Energy 194 (2022) 1261–1276. doi:10.1016/j.renene.2022.05.145.

[22] E. Rosenberg, K. Espegren, J. Danebergs, L. Fridstrøm, I. Beate Hovi, A. Madslien, Modelling the interaction between the energy system and road freight in Norway, Transportation Research Part D: Transport and Environment 114 (1 2023). doi:10.1016/j.trd.2022.103569.

[23] S. Backe, D. Pinel, M. Askeland, K. B. Lindberg, M. Korpås, A. Tomasgard, Exploring the link between the EU emissions trading system and net-zero emission neighbourhoods, Energy and Buildings 281 (2023) 112731. doi:10.1016/j.enbuild.2022.112731.
URL https://linkinghub.elsevier.com/retrieve/pii/S0378778822009021

[24] M. Mimica, D. F. Dominković, V. Kirinčić, G. Krajačić, Soft-linking of improved spatiotemporal capacity expansion model with a power flow analysis for increased integration of renewable energy sources into interconnected archipelago, Applied Energy 305 (1 2022). doi:10.1016/j.apenergy.2021.117855.

[25] D. Romanchenko, E. Nyholm, M. Odenberger, F. Johnsson, Flexibility potential of space heating demand response in buildings for district heating systems, Energies 12 (15) (7 2019). doi:10.3390/en12152874.

[26] M. Mimica, D. F. Dominković, T. Capuder, G. Krajačić, On the value and potential of demand response in the smart island archipelago, Renewable Energy 176 (2021) 153–168. doi:10.1016/j.renene.2021.05.043.

[27] D. F. Dominković, R. G. Junker, K. B. Lindberg, H. Madsen, Implementing flexibility into energy planning models: Soft-linking of a high-level energy planning model and a short-term operational model, Applied Energy 260 (December 2019) (2020) 114292. doi:10.1016/j.apenergy.2019.114292.
URL https://doi.org/10.1016/j.apenergy.2019.114292

[28] R. G. Junker, A. G. Azar, R. A. Lopes, K. B. Lindberg, G. Reynders, R. Relan, H. Madsen, Characterizing the energy flexibility of buildings and districts, Applied Energy 225 (2018) 175–182. doi:10.1016/j.apenergy.2018.05.037.
URL https://doi.org/10.1016/j.apenergy.2018.05.037

[29] R. G. Junker, C. S. Kallesøe, J. P. Real, B. Howard, R. A. Lopes, H. Madsen, Stochastic nonlinear modelling and application of price-based energy flexibility, Applied Energy 275 (10 2020). doi:10.1016/J.APENERGY.2020.115096.

[30] O. Corradi, H. Ochsenfeld, H. Madsen, P. Pinson, Controlling electricity consumption by forecasting its response to varying prices (2013). doi:10.1109/TPWRS.2012.2197027.

[31] M. Z. Jacobson, M. A. Delucchi, Z. A. Bauer, S. C. Goodman, W. E. Chapman, M. A. Cameron, C. Bozonnat, L. Chobadi, H. A. Clonts, P. Enevoldsen, J. R. Erwin, S. N. Fobi, O. K. Goldstrom, E. M. Hennessy, J. Liu, J. Lo, C. B. Meyer, S. B. Morris, K. R. Moy, P. L. O'Neill, I. Petkov, S. Redfern, R. Schucker, M. A. Sontag, J. Wang, E. Weiner, A. S. Yachanin, 100% Clean and Renewable Wind, Water, and Sunlight All-Sector Energy Roadmaps for 139 Countries of the World, Joule 1 (1) (2017) 108–121. doi:10.1016/j.joule.2017.07.005.

[32] K. Hedegaard, B. V. Mathiesen, H. Lund, P. Heiselberg, Wind power integration using individual heat pumps - Analysis of different heat storage options, Energy 47 (1) (2012) 284–293. doi:10.1016/j.energy.2012.09.030.

[33] D. Li, W. Y. Chiu, H. Sun, Demand Side Management in Microgrid Control Systems, in: Microgrid: Advanced Control Methods and Renewable Energy System Integration, Elsevier Inc., 2017, pp. 203–230. doi:10.1016/B978-0-08-101753-1.00007-3.

[34] L. Kotzur, L. Nolting, M. Hoffmann, T. Groß, A. Smolenko, J. Priesmann, H. Büsing, R. Beer, F. Kullmann, B. Singh, A. Praktiknjo, D. Stolten, M. Robinius, A modeler's guide to handle complexity in energy systems optimization (11 2021). doi:10.1016/j.adapen.2021.100063.

[35] A. Papavasiliou, Coupling Renewable Energy Supply with Deferrable Demand, PhD Thesis (2011).
URL https://escholarship.org/uc/item/98384265

[36] L. Söder, P. D. Lund, H. Koduvere, T. F. Bolkesjø, G. H. Rossebø, E. Rosenlund-Soysal, K. Skytte, J. Katz, D. Blumberga, A review of demand side flexibility potential in Northern Europe, Renewable and Sustainable Energy Reviews 91 (2018) 654–664. doi:10.1016/j.rser.2018.03.104.

[37] H. Lund, P. A. Østergaard, D. Connolly, I. Ridjan, B. V. Mathiesen, F. Hvelplund, J. Z. Thellufsen, P. Sorknæs, Energy Storage and Smart Energy Systems, International Journal of Sustainable Energy Planning and Management 11 (2016) 3–14. doi:10.5278/ijsepm.2016.11.2.

[38] P. S. Kwon, P. Østergaard, Assessment and evaluation of flexible demand in a Danish future energy scenario, Applied Energy 134 (2014) 309–320. doi:10.1016/j.apenergy.2014.08.044.

[39] J. G. Kirkerud, N. O. Nagel, T. F. Bolkesjø, The role of demand response in the future renewable northern European energy system, Energy 235 (2021) 121336. doi:10.1016/j.energy.2021.121336.
URL https://doi.org/10.1016/j.energy.2021.121336

[40] S. Ben Amer, R. Bramstoft, O. Balyk, P. S. Nielsen, Modelling the future low-carbon energy systems-case study of greater Copenhagen, Denmark, International Journal of Sustainable Energy Planning and Management 24 (2019) 21–32. doi:10.5278/ijsepm.3356.

[41] S. Charousset, N. Oudjane, P. del Granado, M. Barani, T. Perger, S. Zwickl-Bernhard, H. Auer, L. Olmos, A. Ramos, I. Graabak, E. F. Alvarez, P. Härtel, F. Frischmuth, S. Lepaul, D. Pinel, O. Wolfgang, A. Schledorn, D. F. Dominković, G. Kirkil, E. Celebi, A. Yucekaya, F. Holz, Case study results: openENTRANCE deliverable no. D6.2, Tech. rep. (4 2023).

[42] Plan4res modelling suite.
URL https://openenergymodels.net/models/plan4res-modelling-suite/

[43] D. Beulertz, S. Charousset, D. Most, S. Giannelos, I. Yueksel-Erguen, Development of a Modular Framework for Future Energy System Analysis, in: 54th International Universities Power Engineering Conference, UPEC 2019, Institute of Electrical and Electronics Engineers Inc., 2019. doi:10.1109/UPEC.2019.8893472.
URL https://ieeexplore-ieee-org.proxy.findit.cvt.dk/stamp/stamp.jsp?tp=&arnumber=8893472

[44] D. Beulertz, M. Franken, N. Oudjane, W. van Ackooij, J. Schweiger, I. Konstentelos, P. Djapic, D. Pudjianto, Synergistic Approach of Multi-Energy Models for an European Optimal Energy System Management Tool: Deliverable D 3.1: Description of model interconnections, Tech. rep. (2018). doi:10.5281/zenodo.3904272.
URL https://zenodo.org/records/3904272

[45] M. Cearliani, linear-tree: A python library to build Model Trees with Linear Models at the leaves.
URL https://github.com/cerlymarco/linear-tree

[46] H. Auer, K. Löffler, K. Hainsch, T. Burandt, I. Graabak, S. Schmidt, A. Yucekaya, E. Celebi, G. Kirkil, S. Zwickl-Bernhard, Quantitative Scenarios for Low Carbon Futures of the European Energy System on Country, Region and Local Level, Tech. rep. (2022).
URL https://openentrance.eu/2022/07/06/quantitative-scenarios-for-low-carbon-futures-of-the-european-energy-system-oncountry-region-and-local-level/

[47] openENTRANCE consortium, International Institute for Applied Systems Analysis, openENTRANCE Scenario Explorer.
URL https://data.ece.iiasa.ac.at/openentrance/#/login

[48] S. Charousset, S. Noceir, D. Daniel, N. Oudjane, plan4res public dataset for case study 3 "Cost of RES integration and impact of climate change for the European Electricity System in a future world with high shares of renewable energy sources".

URL https://zenodo.org/record/3802550#.Y_O-si8Q1QI
[49] Dansk Fjernvarme, Fakta om fjernvarme.
URL https://www.danskfjernvarme.dk/presse/fakta-om-fjernvarme
[50] A. Frangioni, N. Iardella, R. Durbano Lobato, The SMS++ Project.
[51] Python Software Foudnation, Python 3.9.11 (3 2022).
URL https://docs.python.org/release/3.9.11/
[52] J. Roy, S. Mitchell, F. Peschiera, PuLP 2.7.0 (2022).
URL https://pypi.org/project/PuLP/
[53] Gurobi Optimization, Gurobi Optimizer Reference Manual (2019).
URL http://www.gurobi.com
[54] J. Forrest, T. Ralphs, H. Gambini Santos, S. Vigerske, L. Hafer, B. Kristjansson, et al., coin-or/Cbc: Release releases/2.10.8 (2022).
URL https://zenodo.org/record/6522795#.Y_VxsC8Q1QI

Appendix

Appendix A. Danish electricity imports

Table A.6: Danish electricity imports in plan4EU in TWh (relative difference to `Ref` scenario). Dark red (blue) colours indicate high absolute growth (reduction) with respect to the `Ref` scenario.

	Ref	DR	HS	DR+HS	Ref.| -10%ES	DR| -10%ES	HS| -10%ES	DR+HS| -10%ES	DR| pr.=0.03	DR| pr.=0.1
GER	6.85 (±0.0%)	6.81 (-0.64%)	6.41 (-6.41%)	6.39 (-6.67%)	6.84 (-0.19%)	6.83 (-0.35%)	6.42 (-6.26%)	6.42 (-6.26%)	6.83 (-0.32%)	6.8 (-0.68%)
NOR	9.68 (±0.0%)	9.72 (+0.39%)	10.06 (+3.9%)	10.1 (+4.25%)	9.67 (-0.17%)	9.67 (-0.15%)	10.03 (+3.54%)	10.03 (+3.54%)	9.72 (+0.35%)	9.73 (+0.42%)
SWE	6.91 (±0.0%)	6.97 (+0.85%)	6.79 (-1.78%)	6.79 (-1.81%)	6.91 (-0.08%)	6.91 (+0.01%)	6.74 (-2.42%)	6.74 (-2.42%)	6.95 (+0.57%)	6.91 (+0.02%)
NL	0.75 (±0.0%)	0.74 (-1.65%)	0.64 (-14.2%)	0.64 (-14.54%)	0.75 (+0.62%)	0.75 (+0.81%)	0.65 (-13.39%)	0.65 (-13.39%)	0.74 (-0.7%)	0.74 (-1.35%)
UK	4.87 (±0.0%)	4.89 (+0.31%)	4.87 (-0.06%)	4.87 (+0.06%)	4.86 (-0.25%)	4.85 (-0.39%)	4.87 (-0.06%)	4.87 (-0.06%)	4.88 (+0.16%)	4.89 (+0.32%)
Total	29.07 (±0.0%)	29.12 (+0.19%)	28.77 (-1.01%)	28.79 (-0.95%)	29.02 (-0.15%)	29.01 (-0.18%)	28.71 (-1.23%)	28.71 (-1.23%)	29.12 (+0.18%)	29.07 (+0.01%)

Appendix B. Danish electricity exports

Table B.7: Danish electricity exports in plan4EU in TWh (relative difference to `Ref` scenario). Dark red (blue) colours indicate high absolute growth (reduction) with respect to the `Ref` scenario.

	Ref	DR	HS	DR+HS	Ref.| -10%ES	DR| -10%ES	HS| -10%ES	DR+HS| -10%ES	DR| pr.=0.03	DR| pr.=0.1
GER	17.9 (±0.0%)	18.03 (+0.72%)	18.4 (+2.8%)	18.41 (+2.85%)	17.88 (-0.13%)	17.93 (+0.19%)	18.33 (+2.4%)	18.33 (+2.4%)	17.99 (+0.53%)	18.03 (+0.72%)
NOR	4.11 (±0.0%)	4.07 (-0.92%)	3.75 (-8.67%)	3.72 (-9.34%)	4.1 (-0.22%)	4.11 (+0.1%)	3.76 (-8.4%)	3.76 (-8.4%)	4.09 (-0.53%)	4.07 (-0.97%)
SWE	11.57 (±0.0%)	11.54 (-0.21%)	11.63 (+0.56%)	11.64 (+0.6%)	11.54 (-0.27%)	11.54 (-0.28%)	11.65 (+0.73%)	11.65 (+0.73%)	11.54 (-0.21%)	11.57 (+0.04%)
NL	5.26 (±0.0%)	5.27 (+0.19%)	5.35 (+1.73%)	5.35 (+1.77%)	5.25 (-0.13%)	5.25 (-0.16%)	5.34 (+1.56%)	5.34 (+1.56%)	5.27 (+0.14%)	5.27 (+0.08%)
UK	6.7 (±0.0%)	6.7 (-0.06%)	6.72 (+0.25%)	6.71 (+0.12%)	6.7 (-0.04%)	6.71 (+0.12%)	6.7 (-0.08%)	6.7 (-0.08%)	6.71 (+0.1%)	6.69 (-0.13%)
Total	45.54 (±0.0%)	45.61 (+0.16%)	45.86 (+0.7%)	45.84 (+0.65%)	45.47 (-0.16%)	45.55 (+0.01%)	45.78 (+0.54%)	45.78 (+0.54%)	45.6 (+0.14%)	45.63 (+0.19%)

Appendix C. Danish heat storage investments

Table C.8: Danish heat storage investments in Frigg.

	Ref	DR	HS	DR+HS	Ref.| -10%ES	DR| -10%ES	HS| -10%ES	DR+HS| -10%ES	DR| pr.=0.03	DR| pr.=0.1
Capacity [GWh]	0.0	0.0	387.78	356.28	0.0	0.0	387.81	356.72	0.0	0.0
Investment cost [M EUR]	0.0	0.0	58.78	54.0	0.0	0.0	58.78	54.07	0.0	0.0

Appendix D. EU electricity mix

Table D.9: EU electricity mix in plan4EU in TWh (relative difference to `Ref` scenario). Dark red (blue) colours indicate high absolute growth (reduction) with respect to the `Ref` scenario.

	`Ref`	`DR`	`HS`	`DR+HS`	`Ref.` | `-10%ES`	`DR` | `-10%ES`	`HS` | `-10%ES`	`DR+HS` | `-10%ES`	`DR` | `pr.=0.03`	`DR` | `pr.=0.1`
Hydro	893.1 (±0.0%)	893.49 (+0.04%)	893.97 (+0.1%)	894.37 (+0.14%)	893.7 (+0.07%)	893.22 (+0.01%)	894.04 (+0.1%)	894.04 (+0.1%)	893.92 (+0.09%)	893.49 (+0.04%)
Nuclear	342.67 (±0.0%)	342.59 (-0.02%)	342.3 (-0.11%)	342.32 (-0.1%)	342.62 (-0.01%)	342.61 (-0.02%)	342.31 (-0.11%)	342.31 (-0.11%)	342.59 (-0.02%)	342.65 (-0.01%)
Wind	1817.5 (±0.0%)	1817.51 (±0.0%)	1818.45 (+0.05%)	1818.29 (+0.04%)	1817.37 (-0.01%)	1817.63 (+0.01%)	1818.33 (+0.05%)	1818.33 (+0.05%)	1817.4 (-0.01%)	1817.46 (±0.0%)
Solar	1092.88 (±0.0%)	1092.81 (-0.01%)	1093.16 (+0.03%)	1092.84 (±0.0%)	1092.48 (-0.04%)	1092.9 (±0.0%)	1092.93 (±0.0%)	1092.93 (±0.0%)	1092.56 (-0.03%)	1092.84 (±0.0%)
Biomass	240.76 (±0.0%)	240.67 (-0.03%)	240.14 (-0.26%)	240.15 (-0.25%)	240.76 (±0.0%)	240.72 (-0.01%)	240.14 (-0.26%)	240.14 (-0.26%)	240.65 (-0.04%)	240.67 (-0.04%)
Hydrogen	143.43 (±0.0%)	143.34 (-0.06%)	142.72 (-0.49%)	142.71 (-0.5%)	143.39 (-0.02%)	143.41 (-0.01%)	142.77 (-0.46%)	142.77 (-0.46%)	143.37 (-0.04%)	143.34 (-0.06%)
Natural gas	205.36 (±0.0%)	205.35 (±0.0%)	205.01 (-0.17%)	205.04 (-0.16%)	205.4 (+0.02%)	205.38 (+0.01%)	205.1 (-0.13%)	205.1 (-0.13%)	205.37 (±0.0%)	205.34 (-0.01%)
Total	4735.7 (±0.0%)	4735.77 (±0.0%)	4735.75 (±0.0%)	4735.72 (±0.0%)	4735.72 (±0.0%)	4735.86 (±0.0%)	4735.62 (±0.0%)	4735.62 (±0.0%)	4735.86 (±0.0%)	4735.79 (±0.0%)