A review of co-optimization approaches for operational and planning problems in the energy sector

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HIGHLIGHTS

- Co-optimization for power system operation and expansion planning is reviewed.
- The majority of short-term studies have grown up around energy and reserve markets.
- Co-optimization might lead to less costly solutions than traditional techniques.
- The need to coordinate the necessary data from multiples actors is a challenge.
- Integrating supply and demand-side options has been recognized as a current need.

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ABSTRACT

This paper contributes to a comprehensive perspective on the application of co-optimization in the energy sector – tracking the frontiers and trends in the field and identifying possible research gaps – based on a systematic literature review of 211 related studies. The use of co-optimization is addressed from a variety of perspectives by splitting the studies into ten key categories. Research has consistently shown that co-optimization approaches can be technically challenging and it is usually a data-intensive procedure. Overall, a set of techniques such as relaxation, decomposition and linear approaches have been proposed for reducing the inherent nonlinear model's complexities. The need to coordinate the necessary data from multiples actors might increase the complexity of the problem since security and confidentiality issues would also be put on the table. The evidence from our review seems to suggest a pertinent role for addressing real-case systems in future models instead of using theoretical test cases as considered by most studies. The identified challenges for future co-optimization models include (i) dealing with the treatment of uncertainties and (ii) take into account the trade-offs among modelling fidelity, spatial granularity and geographical coverage. Although there is also a growing body of literature that recognizes the importance of co-optimization focused on integrating supply and demand-side options, there has been little work in the development of co-optimization models for long-term decision-mak-ing, intending to recognize the impact of short-term variability of both demand and RES supply and well suited to systems with a high share of RES and under different demand flexibility conditions. The research results represent a further step towards the importance of developing more comprehensive approaches for integrating short-term constraints in future co-optimized planning models. The findings provide a solid evidence base for the multi-dimensionality of the co-optimization problems and contribute to a better understanding of how future operating and planning models might be affected under the use of such co-optimization approaches.

1. Introduction

The increasing search for energy pathways towards climate change and social wellbeing has led to a shift of strategies and policies, favouring Renewable Energy Sources (RES) and Energy Efficiency Measures (EEMs) but also underlying the security of electricity supply as the main pillars of the energy policies in the energy sector [1,2]. The global energy sector has been witnessing rapid changes mainly due to

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the fast-paced technological advances. Recent technological advances coupled with the recent environmental and social challenges have also heightened the need to use more holistic and integrated approaches to meet these goals simultaneously. The past few years have witnessed, in particular, rapid advances in the field of smart grids technologies which enable the integrated operation among a set of different resources [3,4]. These new conflicting aspects surrounding energy systems increased the search for solutions that take into account the trade-offs between climate neutrality goals but at the same time envisaging a "*just energy transition*" [5,6].

The energy planning process describes a procedure with a high level of complexity due to the existence of many conflicting aspects, including environmental, technological, social and economic ones that should be considered in the renewable energy decision-making process [7–9]. Specifically, the electricity planning has become more complex due to a set of factors, namely the growing share of RES, specifically those RES with variable output [10]; the need for reliability and security of supply; fuel-increasing prices and fuel supply security; regional job creation; climate concerns; among others. Ref. [9] mention that the inclusion of RES in energy planning is a complicated task and has to surpass eco- nomic, social, technical, environmental, and institutional barriers. Several uncertainties are also involved in the long-term energy planning process, such as economic growth, government policies, technological development, energy efficiency, and demand-side concerns. The role of storage in power systems with a high share of renewables should also be put on the table in the context of the energy transition [11]. These features together might define the pathways in which the energy mixwill be deployed in the future. Over the past years, we have also wit- nessed a significant trend towards exploring not only the supply-sideoptions but a strong growth has been placed on exploring the flexi- bility potential from the demand-side, which has also been disrupting traditional energy planning models. DR has emerged as a valuable resource flexibility option for balancing supply and demand and consequently enhancing the overall level of power systems' flexibility.

There is a large number of published studies (e.g., Refs. [12–14]) suggesting that investments in DR strategies would avoid investments in the supply side. The benefits brought by DR may contribute significantly to the power system operation and deferring investments in distribution and transmission systems. DR has also been considered a powerful toolto contribute to the future challenges of integrating VRE resources into the power grid and even partially releasing energy network stress. DR may also support supply shortages and load growth control [15], decrease the maximum interconnection capacity, and optimize resource allocation [16].

Along with the past years, new studies have been published addressing the different faces surrounding both operational and plan- ning aspects within the energy field by using different modelling ap-proaches. Several studies in the energy field have been carried out using optimization approaches for modelling both short (e.g. [17,18]) and long-term (e.g. [19–22]) problems. Extensive research has been con- ducted, for example, in economic dispatch [17] and unit commitment problems [18], Generation Expansion Planning (GEP) [19,23,24], Transmission Expansion Planning (TEP) [20,25], integrating RES into GEP problems [21] and modelling and simulation of energy systems [22], which are among the most commonly exploited research topics in the field. The need to correlate operational and planning decision- making into long-term planning frameworks has also been identified as a current trend in the literature (see, for example, Ref. [26] and Ref. [27]).

The particular use of optimization models has been extensively addressed over the literature to address such operational and planning problems supporting the decision-making process of electricity supply, transmission investments and policy designs [28,29]. The goal for traditional optimization models is to find in a set of solutions the best one that minimizes or maximizes the value of an objective function [30]. Although traditional planning approaches have a tendency to address both operational and expansion planning problems individually, co-optimization may play a central role in the development of integrated approaches for operational and planning energy-related strategies. Therefore, a growing body of recent literature has focused on the use of co-optimization approaches within the energy field. Co-optimization models are computer-aided decision-support tools that search, in a set of solutions (defined by constraints), the best one in terms of a defined objective function, considering operational and planning energy-related strategies [31]. The term "*co-optimization*" has been also commonly referred to as "*co-planning*" [32–40], "*joint optimization*" [41–43], "*simultaneous optimization*" [41,44], "*combined optimization*" [29,45] or even "*co-scheduling*" [46]. We also highlight that many research works have used the term "*optimization*" to refer to "*co-optimization*" problems. This means that these terms have been often used interchangeably and without high precision in the energy sector.

Since the definition of co-optimization varies among researchers, it is essential to clarify how this concept has been used in the energy field. According to a definition provided by Ref. [31], "*co-optimization is the optimization of two or more different yet related resources within one planning framework*". Co-optimization approaches aim to find the best solution in terms of cost or other objectives while satisfying a set of constraints such as economic, technical, and environmental ones [28,31]. Ref. [31] also provides a more general definition focused on electric systems planning. This broader definition refers to co- optimization as "*the simultaneous identification of two or more classes of investment decisions within one optimization strategy*". The authors point out that *"classes of investment decisions, in the context of electric systems planning, almost always include decisions to build generation and trans- mission. But they may include other types of decisions as well, such asdemand-side solutions, decisions to install storage, or building of natural gas pipelines. "One optimization strategy" may consist of a formulation to solve a single optimization problem (*e.g.*, minimize cost subject to constraints) or itmay consist of a formulation to solve an iterative series of optimization problems (*i.e.*, sequential yet coordinated generation and transmission planning)*".

Therefore, the application of co-optimization approaches within the energy sector has attracted considerable attention in the past few years, mainly because of its potential benefits and synergies that could yield low-cost solutions and improve resource usage compared to traditional decoupled optimization approaches. Although the established practicehas been to design generation planning first and further to plan trans- mission, in a co-optimization model, in general, both (generation andtransmission) are assessed simultaneously to identify integrated solu- tions. Significant analysis and discussion on the use of co-optimization of electricity transmission and generation resources for long-term planning purposes have been addressed by previous research. Ref. [28], for instance, focused on reviewing the concepts and modelling approaches from the use of co-optimization approaches on electricity transmission and generation resources for planning and policy analysis, including supply-side resources, demand-side resources, transmission options and natural gas pipelines. The review efforts of Ref. [28] are centred on the existing and emerging co-optimization models for the joint optimization of generation and transmission (focused on the optimizers, data, modelling fidelity and computational requirements). A particular state- of-the-art review of the generation expansion planning problems is addressed by [47], highlighting the increasing use of co-optimization approaches in this category of problems. In a comprehensive literature review of the modelling approaches from the joint planning of power and natural gas networks coordination, the authors of [48] highlighted the cumulative synergies in the coupling of power and gas systems.

Therefore, a growing body of literature recognizes the importance and critical role played by co-optimization in the energy sector and electricity markets. However, previously published studies on the sub- ject have been mostly restricted to particular review analyses. The co- optimization might also involve other types of decisions such as sup-ply and demand-side integration, energy and reserve markets, water-

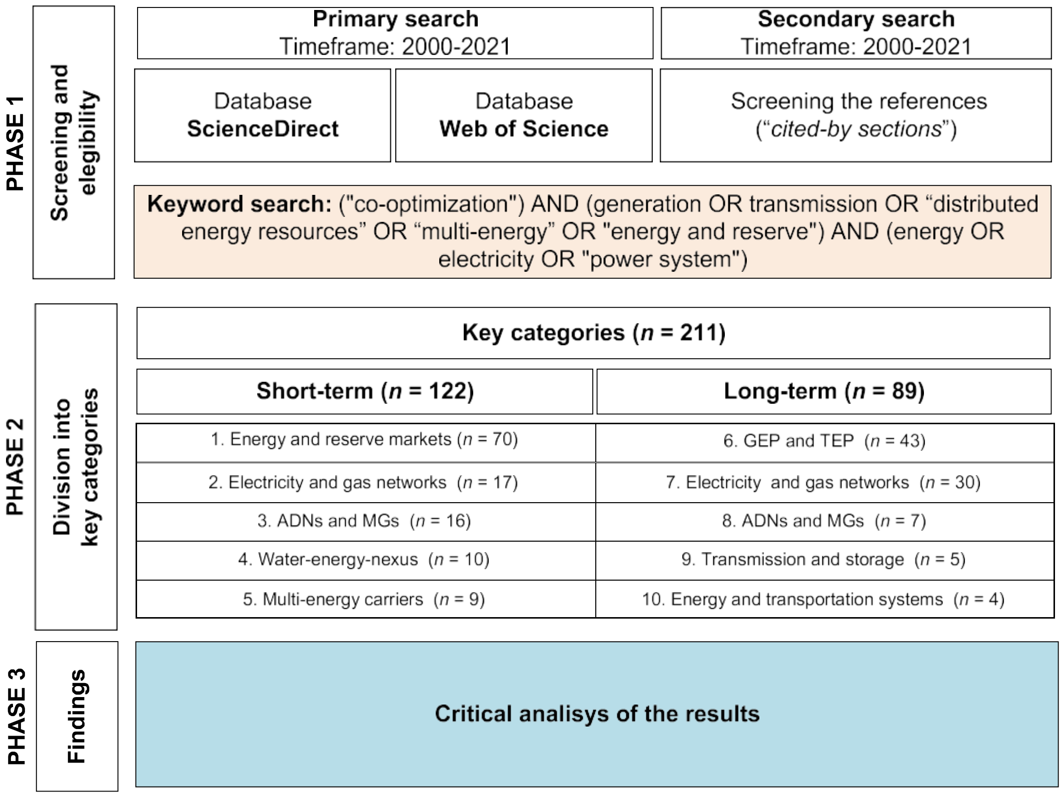

Fig. 1. Detailed methodological approach of the research.

energy-nexus, power grid and Natural Gas (NG) networks and multi-energy carriers (e.g., electricity, gas, and district heating systems), just to name a few. Most of the work carried out on the topic lacks on providing a general review analysis covering both operational and expansion planning problems in the energy sector and its interrelations, which are very appealing to consider in future energy models. The contribution of the present study to the literature is multifold and isstrengthened by the following key accomplishments: (i) a comprehen- sive literature review of the most relevant research into the use of co- optimization for power system operation and expansion planning problems is addressed. We attempt to shed new light on the topic by tracking the frontiers and trends in the field by analyzing 211 related studies. Then, the (ii) identification of the latest research progress and possible research gaps for both operational and planning future co- optimization problems is performed, supporting future research pathways.

The remainder of the paper is organized as follows. This first section introduces the topic under study, highlighting the importance of both optimization and co-optimization approaches in the energy field and clarifying the difference between these concepts. Section 2 discusses the specific methods by which the research and analyses were conducted. The paper proceeds investigating the most relevant published research in Section 3. Section 4 draws together the various strands of this study and Section 5 identifies areas for further research.

2. Methodology

This research consisted of an extensive and systematic literature review of the different types of co-optimization approaches used in the energy field. Co-optimization approaches may be classified according to different categories. In this paper, we follow two basic approaches currently being adopted in research into co-optimization within the energy field. The first one is focused on the short-term (i.e., associated with power system operation or operation planning problems) and the second-largest focus has been on the long-term assessments (i.e., associated with power system planning which is also referred to as investment planning problems). Therefore, this investigation used archival data and it can be classified as an exploratory study regarding its nature. The general methodological approach followed in this research is illustrated in Fig. 1.

The primary literature research data were selected from two central databases: Web of Science and Science Direct (Phase 1). An additional step has been performed by screening the primary research references (Phase 1 – secondary search). This process is considered essential since different terms have been used to refer to co-optimization and a great deal of important previous published research has been found in this screening process. Studies over the past two decades have provided important information on the use of co-optimization approaches in the energy field, and therefore, the chosen timeframe is from 2000 to 2021. The selected keywords used to locate peer-revied journals are also illustrated in Phase 1. The most relevant published research was iden- tified and divided into ten key categories (Phase 2) considering the in- teractions among the different sectors involved (i.e., electricity, gas, heat, water and/or transportation) such as better illustrated in Fig. 2.Two hundred and eleven studies were fully reviewed. A holistic inves- tigation of each key category is undertaken along with Section 3. Finally,a critical analysis of the results is undertaken in Phase 3.

3. Synthesis of co-optimization approaches in the energy field

A state-of-the-art review of high-quality research is addressed in this section regarding the use of co-optimization approaches in the energy field. Section 3.1 will focus on assessing co-optimization studies in the short-term, whereas Section 3.2 addresses the most relevant research on long-term co-optimization models. Appendix A will present a table summarizing the central studies in each category by splitting it into the year of publication, sector, spatial resolution, planning horizon, objec- tive, programming/tool and whether or not the term ‘*co-optimization*’ is

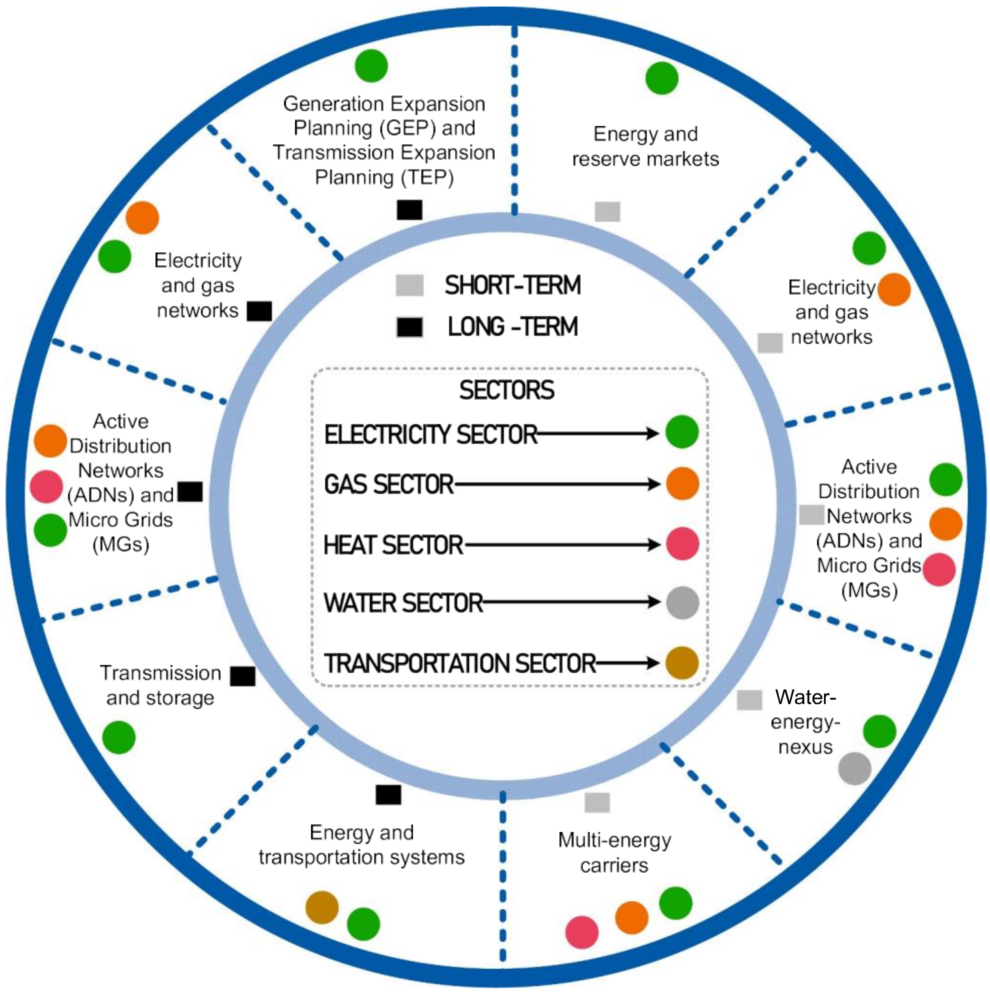

Fig. 2. Categories of co-optimization research studies.

explicitly mentioned in each study.

3.1. Co-optimization in the short-term (operational decisions)

3.1.1. Co-optimization between energy and reserve markets

The role developed by renewable energy as a new actor in participating in ancillary services[1] (AS) markets has been considerably growing in the context of liberalized electricity markets [49]. This means that simultaneous co-optimized approaches for energy and ancillary services dispatch are supposed to be more efficient than traditional approaches (i.e., sequential and simultaneous dispatch-based approaches) [49]. Co-optimization of energy and reserve markets has been largely addressed by previous research works, as illustrated in Table A1 (Appendix A). "*Co-optimization of energy and ancillary services*" has also been referred in the literature as "*co-optimization of energy and reserve requirements*". Therefore, "*ancillary services*" and "*reserve requirements*" have been often used interchangeably. The co-optimization of energy and reserve markets is also sometimes referred to as "*joint dispatch*", such as in Ref. [50].

Short-term economic dispatch and energy reserve models generally use a high temporal resolution [51] with a particular focus on the minimization of the costs [42,51], such as in [52–58]. Ref. [42] highlighted that "*the objective of joint optimization is to minimize the total cost of providing sufficient capacity to meet forecast demand for both energy and ancillary services*". The authors of Ref. [59] underline that *"co-optimized reserve and energy markets involve the simultaneous determination of a price for electricity and a price for each category of reserve"*. A set of principles for the efficient electricity market design was addressed by [60], highlighting the co-optimization of energy and reserve resources (i.e., scheduled and dispatched simultaneously) to maximize social welfare as one of the six principles for the efficient electricity market design.

A two-stage stochastic programming model has been developed by Ref. [61], aiming to optimize the schedule of energy and reserve mar-kets. The co-optimization between energy and reserve markets in sys- tems with high shares of wind power is adressed by Ref. [62] through a two-stage stochastic programming model. A stochastic co-optimization approach is also followed by Ref. [63] focused on the maximization of the expected profit from energy and reserve markets for systems with multiple hydropower plants. Ref. [63] addressed a co-optimization model for energy and reserve markets from the perspective of a hydro- power system that simultaneously participates in both the day-aheadand the secondary regulation reserve market. Similarly, Ref. [64] addressed the stochastic short-term hydrothermal scheduling problem by co-optimizing energy and reserves.

An optimal bidding strategy has been considered by Ref. [65] through a two-stage stochastic programming approach in day-ahead and real-time markets. Co-optimizing energy and ancillary services dispatch in day-ahead and real-time markets is also addressed by Ref. [66]. To

[1] Ancillary services typically include the scheduling, system control and dispatch; voltage control; regulation and frequency response; energy imbal-ance; operating spinning reserves and operating supplemental reserves [42].

further examine the role of a prosumer's aggregator in energy and secondary reserve markets, Ref. [67] developed a two-stage stochastic optimization bidding strategy. In a follow-up study, a two-stage stochastic optimization approach was developed by Ref. [68] to participate in providing energy and reserve markets under uncertainty in Micro Grids (MGs). Along the same lines, Ref. [69] dealt with the provision of energy, reserve and reliability services for multi-energy MGs following a co-optimization approach. To further investigate the optimal scheduling of Distributed Energy Resources (DERs) in standalone micro-grid systems, Ref. [70] developed a co-optimization model through a risk-based stochastic approach for the simultaneous scheduling of energy and reserve of DERs. The use of DER has become a valuable solution to respond to the several problems brought about by the growth of VRE and thus contribute to enhancing the flexibility in grid operations. The world has been moving towards renewable-based DER mainly because of two key factors (i) the decreasing costs of these technologies and (ii) the increasing need for new energy flexibility requirements in power systems [71]. The introduction of DER also holds the potential to address the three main conflicting variables (i.e., cost, the security of supply, and CO_2 emissions reduction) faced by governments, municipalities, industries, and communities in general for which a holistic and integrated approach is required to meet these goals simultaneously. Regardless of all the benefits related to the development of DER (e.g., the grid losses reduction and the postponing of conventional investments in infrastructure), the growing insertion of these technologies implies more uncertainties on power demand projections by also affecting the optimal future countries' energy mix [72]. The authors of Ref. [73] underline that *"distributed energy resources (DER) are driving the need to change how the grid is managed"*. Therefore, DER represents a high disruptive potential and it can add up significant and systemic benefits to the power system but at the same time, it may significantly increase the power system's complexity.

Ref. [74] developed a unit commitment model based on a co-optimized approach for energy and reserve markets, particularly well-suited for systems with high wind power penetration. The proposed model also incorporated both a large-scale energy storage system and an improved Demand-Response (DR) program. A new method for evaluating the optimal scheduling for the joint operation between wind power plants and pump storage in the energy and ancillary markets is proposed by [75] through a stochastic optimization approach.

Co-optimization between energy and ancillary services is also addressed in [76], focusing on the flexibility provided by Concentrating Solar Power (CSP) plants with thermal energy storage. Ref. [77] presented a co-optimization model that values energy storage in both electricity and ancillary service markets. The investigation of the energy storage value for both energy and ancillary markets is studied by [78] for multiple markets, including day-ahead, real-time and ancillary markets. A DR model in co-optimized day-ahead energy and spinning reserve market has been proposed by [79] using a Mixed-Integer Linear Programming (MILP) approach. The load flexibility is utilized by price responsive bids in the energy market, while spinning reserve bids are used in the reserve market in the model proposed by Ref. [79]. The co-optimization of energy and spinning reserves has also been tackled in the work of [80] under a deterministic security criterion. The particular co-optimization of energy and non-spinning reserve has been tackled by Ref. [81] through a randomized optimization technique based on an IEEE 30-bus system. The authors of Ref. [81] also included in their model formulation constraints such as ramping limits, N-1 security and generation minimum on and off times.

Co-optimization of energy and reserve markets for integrated electricity-gas networks has also caught the attention of recent research. The integrated power and gas networks assessment with energy storage systems has been undertaken by Ref. [82] based on the co-optimization of energy and reserve markets. Ref. [83] proposed an energy-reserve co-optimization model for electricity and natural gas systems in the presence of multiple reserve resources.

The simultaneous dispatch between energy and reserve for isolated systems has also attracted recent research work. Ref. [84], for instance, developed a day-ahead energy and capacity scheduling stochastic co-optimization model by combining energy, reserve capacity and primary regulation markets and well suited for isolated power systems with large shares of electric vehicles.

Ref. [57] developed a model focused on providing Dispatchable Transmission Services (DTSs) in stochastic joint energy and spinning reserve markets. The joint scheduling of energy and reserve is further proposed by Ref. [85] focused on hybrid AC/DC transmission grids and under wind power uncertainty. A co-optimization model for energy and reserve market is investigated in [56] by incorporating post-contingency transmission switching. The main goal, in this case, is to reduce both the operating costs and the power outages when a contingency occurs [56]. Ref. [86] developed a co-optimized dispatch model well suited to the identification of Compressed Air Energy Storage (CAES) in energy and reserve markets in multiple United States regions. The coordination between generation and a pumped-hydro storage system is addressed in [87] through a co-optimized energy/regulation environment.

An optimal self-scheduling model for the profit maximization of a power company is developed by [88] using a MILP model and taking the primary, secondary and tertiary reserve markets into account. The use of co-optimization between energy and reserve markets for combined power distribution and district heating networks has been addressed by Refs. [89,90], for example. In particular, day-ahead co-optimization of energy and reserve for combined distribution networks of power and district heating was dealt by Ref. [89] for the Barry Island system under a linear optimization model, which has been considered to minimize the sum of energy and reserve dispatch costs of Combined Heat and Power (CHP) units. Co-optimization of integrated electricity and heating systems was also investigated by Ref. [90], taking the wind uncertainty into account. The model addresses a master problem and a sub-problem solved through a MILP model with its Karush-Kuhn-Tucker (KKT) conditions.

A model for co-optimization of energy and reserve, taking the contributions from both the supply and demand-side into account, has been developed by Ref. [58]. The authors concluded that demand-side participation in providing reserve services might significantly decrease the overall electricity production costs. In [91], a new algorithm has been proposed for energy and spinning reserve scheduling by also taking the demand side contribution into account. A co-optimization DR-energy-spinning reserve market model has also been developed by Ref. [92], which assessed the impact of DR on energy and spinning reserve market prices.

3.1.2. Co-optimization between electricity and gas networks

Other recent studies also provided pathways related to the short-term co-optimization of electricity and gas systems (Table A2 – Appendix A). The co-scheduling between electrical energy and natural gas systems, for example, is addressed in [46]. A model for the coordination between gas and electricity in competitive markets has been tackled by Ref. [93] based on the case of a company that participates in both gas spot and electricity markets. A stochastic co-optimization model is developed in [94] for electricity and natural gas systems focused on systems with high shares of both Electric Vehicles (EVs) and Variable Renewable Energy (VRE) sources. A day-ahead scheduling solution for district integrated natural gas and a power system with high wind power penetration is addressed in [95] using a stochastic MILP model (IEEE 33-bus distributed system) and taking the demand flexibility and CAES into account.

The optimization between interconnected power grids and natural gas networks has also been addressed in [45]. However, this previous research work neglected the dynamics[2] of natural gas systems in their modelling approach. Further research attempted to include these dynamic issues into their modelling approaches, such as in [96,97]. A coupled dispatch optimal control strategy for the coordination of large- scale interconnected electrical and natural gas transmission networkshas been addressed by [96] for the interconnected Illinois system taking into account the dynamics of natural gas systems. The model also allows capturing the spatiotemporal interactions between both gas and electric transmission systems. Their findings revealed that coordinating the dispatch of both systems enabled larger amounts of natural gas to be dispatched to the power grid than the uncoordinated operation [96].The co-optimization between gas and electricity network is also addressed by Ref. [98], capturing the intra-day variations of gas supply and demand through hourly steps temporal resolution.

A day-ahead coordinated co-optimization scheduling approach for interdependent power and gas networks is addressed in [99]. Findings of [99] revealed that using Power-to-gas (PtG) technologies facilitates the insertion of higher renewable energy shares for the energy system evaluated. The integration between electrical and natural-gas systems with PtG technology is also addressed by [100] under an integrated approach by taking the uncertainties from wind and photovoltaic systems into account. The inclusion of the PtG technology and a DR pro- gram is further considered by [101], which proposed a novel hybrid framework for co-planning between electricity and gas systems.

3.1.3. Co-optimization in Active distribution networks (ADNs) and micro grids (MGs)

A great deal of previous research into short-term co-optimization approaches has focused on Active Distribution Networks (ADNs) and Micro Grids (MGs) (see Table A3 – Appendix A). A co-optimization approach is followed in [102] to sizing DG in a hybrid network (electricity/gas/heat). Ref. [44] proposed a robust energy procurement strategy for MG operators with a particular focus on smart grids with hydrogen energy resources. The simultaneous optimization of profits for both the MG operator and consumers is aimed at the proposed energy procurement strategy proposed by Ref. [44]. Ref. [103] developed a coordinated long and short-term Mixed-Integer Nonlinear Programming (MINLP) model focused on MG expansion planning. The model mini- mizes both long-term investment and operational costs (short-term). A co-optimization framework is proposed by Ref. [104] focused on a MG composed of solar PV, transmission switching and emergency genera- tion. Co-optimization of thermal and electrical MG systems is addressed in [105], focusing on a large university campus.

A three-level co-optimization model for reconfiguration, dispatching, and reserve for multiple micro energy grids are addressed explicitly by Ref. [106] modelling an IEEE 37-bus distributed system with an 8- node natural gas system (Shenzhen park in China). The model objec- tives included achieving the minimum loss load rate (1st level); the maximum comprehensive benefit (2nd level) and the minimum reserve cost (3rd level), making use of heuristic algorithms (chaotic ant colony- based approaches). The temporal resolution used in the model of [106] includes (i) day-ahead – focused on capacity reconfiguration; (ii) intra- day – focused on energy dispatching and (iii) real-time – focused on reserve balance issues.

Co-optimization in MGs in the presence of Plug-in Electric Vehicles (PEVs) is addressed by Ref. [107]. The co-optimization among DG units, Battery Energy Storage Systems (BESS) and Electric Vehicle Charging Stations (EVCSs) was addressed by [108] focused on a deterministic network topology. An optimal planning framework has been developed by [109] through a Mixed-Integer Second-Order-Cone Programming (MISOCP) model for ADNs. This last model co-optimizes Distributed Energy Storage Systems (DESS) operation and incorporated a set of emerging technologies, including smart inverter-based DGs – which provide reactive power capability and short-term network reconfiguration. The co-optimization among repair, reconfiguration, and DG dispatch is addressed in [110] through a two-stage outage management model for distributed power systems to minimize the repairing time and maximize the picked-up loads. More recently, the use of Distribution Locational Marginal Prices (DLMPs) had been considered by [111] to schedule DERs in distribution networks optimally.

3.1.4. Co-optimization in water-energy-nexus

A large number of published studies deal with water-energy nexus (also referred to as power-water nexus) co-optimization problems (see Table A4 – Appendix A). The vast majority of studies on water-energy nexus co-optimization have been focused on the short-term (usually day-ahead strategies), i.e., associated with operational energy-related strategies.

A co-optimization modelling approach to deal with water-energy systems at a community scale is proposed in [112]. A conceptual framework representing the energy-water nexus interdependencies is developed by [113] for the Greek power system. The authors of [114] focused on the energy-water nexus design and operation problem by developing a decision support framework well suited for urban resource planning.

Short-term power and water co-optimization models have also been proposed focused on unit commitment [115] and economic dispatch [116–118] approaches. A multi-plant real-time economic dispatch of energy-water nexus is addressed in [116] based on a co-optimization approach. The energy-water unit commitment co-optimization prob- lem is dealt with in [115] by also including the synergistic benefits of introducing renewable energy generation within the modelling approach. A day-ahead economic dispatch co-optimization model for integrated water-energy MG systems was recently proposed by [118]through a MILP model to minimize the energy consumption from the water-energy MG system.

3.1.5. Co-optimization in multi-energy carriers

Recent research has also focused on co-optimization in multi-energy carriers (see Table A5 – Appendix A). The co-optimization of multi- carrier energy resources may offer a set of advantages such as perfor- mance improvements and cost savings, for example [119]. Co- optimization approaches for integrating electricity, gas, and heat net- works have been considered in previous research, such as in [45,120–122]. The optimal scheduling for a multi-energy electricity- heating-gas island system is developed by [120], considering inter- and intra-hour timescales simultaneously. The integration among electricity, gas, and heat networks is modelled by [121] focused on the unit commitment problem and minimizing the total system operation cost. Multiple energy storage technologies (power, gas and thermal) were also included in the modelling framework of [121], which are found to reduce by near 20% the total system's operation cost primarily because the Energy Storage System (ESS) reduced the effect of wind power un- certainty. Future cost-optimal pathways for the city of Aarhus (Denmark) are investigated by [123] in which the production of elec- tricity and heat is co-optimized with the heat storage operation. The particular cases of co-optimization between heat and electricity systems are also illustrated in Table A5 (Appendix A) (see [123–125]).

3.2. Co-optimization in the long-term (expansion planning problems)

3.2.1. Co-optimization in generation-transmission expansion

The planning of a power system is considered a complex

[2] Steady-state modelling approaches have been not considered suitable for long-term planning studies of co-optimization of interconnected power grid and natural gas networks [96,291].

optimization problem [29]. Power system expansion planning problems are usually divided into three main categories: Generation Expansion Planning (GEP[3]), Transmission Expansion Planning (TEP) and generation-transmission co-expansion [126]. However, for the pastthree decades, studies on expansion planning problems have been mostly restricted to the independently planning of generation and transmission. However, these conventional planning approaches can lead to sub-optimal results [47].

GEP and TEP planning problems have been extensively addressedover the literature considering the modelling of national or regional- scale power systems [126]. These studies can be categorized into three main modes, i.e., (i) single-stage (or static) [127] or multiple-stage [128] problems; (ii) conventional mathematical programming or *meta*-heuristic optimization methods [126]; and (iii) transmission expansion only (subject to a static scenario of generation investment); generation expansion only (generation investment subject to a static transmission system) or even both generation and transmission expansion plan [31,126]. Traditionally, GEP and TEP models have been modelled separately [19], i.e., these planning models have typically applied single-stage models to address power system expansion by firstly plan- ning the generation and then the transmission planning is designed to meet this supply as in [19,20,129–131]. These separately modelling approaches have been performed mainly because the investment de- cisions are made independently [19], typically from non-verticallyelectricity markets.

Although GEP and TEP have been usually characterized by sequential optimization [132], the benefits brought about by the simultaneous co-optimization between generation and transmission resources have been highlighted by recent research works [132]. There are a large number of recently published studies that deal with generation-transmission[4] co-optimization problems (see Table A6 – Appendix A). Typically, these models aim to find the least-cost power system configuration for a given period. In the proactive approach, both systems (i.e., GEP and TEP) are co-optimized simultaneously[5], whereas, in the reactive approach, the GEP problem is firstly solved, followed by the TEP prob- lem [133,134]. The simultaneous co-optimization of generation and transmission expansion plans might provide long-term co-optimized expansion planning [135–137]. The advantages of co-optimizing generation and transmission have been addressed by [132]. The authors of [132] compared the sequential versus co-optimized generation and transmission expansion planning approaches and concluded that economic benefits might be achieved through the integrated planning between generation and transmission systems. Refs. [137,138] also highlighted that cost savings would be achieved through generation-transmission co-optimized approaches. A broadly similar point has also recently been made by [28], which reviewed the co-optimization between transmission and generation resources for planning purposes highlighting that planning generation and transmission independentlymight be sub-optimal. Other studies, however, hold the view that "*pro- active transmission expansion decisions may lead to suboptimal solutions when the generation expansion equilibrium problem have multiple solutions (*i.e.*, leading to higher total costs and lower social welfare)* [139]".

Ref. [139] proposed a methodology to address the problem of proactive expansion planning over generation expansion decisions focused on deregulated electricity markets. The benefits of co-optimizing transmission and generation investments under a proactive approach and RES integration into the generation mix are addressed in [137] for the United States Eastern interconnection. A further study [126] used a Mixed-Integer Programming (MIP) generation and transmission expansion co-optimization model considering a high windpower penetration rate for the United States Eastern system. The futureof the United States electricity system is also evaluated in [140] for the year 2050 by splitting the country into 13 regions and using an extended version of the Open Source Energy Modelling System (OSeMOSYS) model. The impact of RES integration on transmission expansion plan- ning was assessed in Ref. [134] through a 10-year co-optimization model based on an hourly resolution approach for supply and demand (IEEE 24-bus test system). The authors employed the multivariate interpolation method to estimate the operational costs to reduce the high computational time associated with the hourly resolution model [134]. The authors of [141] also proposed a new dynamic model for the simultaneous expansion of generation-transmission planning based on two case studies, i.e., a 6-bus and the IEEE 30-bus system. Ref. [141] converted the original MINLP model into a MILP model through the Benders decomposition technique.

The co-optimization between generation and transmission planning for maximizing large-scale solar PV integration is addressed in [142].Ref. [36] explored the role of Concentrating Solar Thermal for the Australian National Electricity Market based on a scenario-based approach. The authors of Ref. [36] highlighted that most previous co- planning models between generation and transmission expansion plan- ning do not use high temporal resolution. Therefore, the hourly tem- poral resolution model is considered one of the main advantages of the proposed model in [36]. The procedure carried out by [126] is based upon a generation and transmission expansion co-optimization problem using a MIP formulation considering wind power and load variations on a large-scale power system. A co-optimization expansion planning model for 2030 is developed for the Chilean power system by assessing the impact of electric vehicles penetration in the country [143].

The importance of co-optimization between generation and transmission in China was investigated in [144] through a linear program- ming approach. The authors highlighted the need of using such a co-planning approach, particularly because the best wind and solar re- sources are located far from the load centres in the country. Two linear optimization models (a load-matching and a cost-minimizing proced- ure) were compared in the work of [29] for power systems with high shares of wind and solar power with storage facilities and simulta- neously designing a High-Voltage Direct-Current (HVDC) transmissionsystem. The modelling of the HVDC transmission system is considered one of the biggest challenges of the proposed model. The first model is a load-matching optimization, and the second model minimizes the annual overall system costs. The benefits and disadvantages of both approaches are discussed, and the most efficient method is shown. The authors concluded that the cost-minimization optimization technique seems to have the most real-world application, although the computa- tional effort largely increases. Findings of Ref. [29] also revealed that linear optimization techniques are well suited to represent an electrical power system from a high-level without the complexity brought about by mixed-integer or nonlinear programming.

Several models have been proposed addressing the integration between GEP and TEP problems with storage under co-optimization approaches (see [29,145–149]). A least-cost co-optimization model has been developed by Ref. [148], dealing with the capacity expansion problem focused on the European energy system. The hourly model also includes transmission and storage constraints. Cost-optimal pathways are also evaluated in [279] for the Association of East Asian Nationsregion, taking the generation, transmission and storage technologies into account. The main advantage of the proposed model comes from the high temporal and spatial resolutions. The results from modelling only

[3] As stated by [292], GEP is a very complex problem mainly in the long-term planning and is usually defined as "*the problem of determining when, what and where the generation plants are required so that the loads are adequately supplied for a foreseen future*".

[4] Also referred to as (i) Transmission and generation capacity expansion planning (TGEP) [139]; (ii) GEPTEP co-optimization models [138]; (iii) Proactive expansion planning [139] or even (iv) Anticipative transmission expansion planning [139].

[5] Ref. [139] highlight that "*in centralized TGEP problems, generation and transmission capacity expansions are simultaneously optimized by a single entity that maximizes social welfare or minimizes the total investment and operation cost*".

generation and transmission with the case in which the ESS devices are included in the co-optimization model has been assessed by Ref. [146]. The authors compared the results with the traditional sequential in- vestment model in which generation and transmission are first made andthen the ESS decisions are defined. Findings of [146] revealed that co- optimizing ESS investments might be a cost-effective option for the power system evaluated. The results also revealed lower curtailment and investment deferrals when the co-optimization approach is followed. The least-cost pathways to decarbonize the Canadian electricity systemis addressed by [145] through a long-term co-optimization of GEP and TEP with the presence of storage. The authors employed a new linear programming-based model that minimizes the overall annual electricity system costs in new generation, transmission and storage facilities [145]. Findings of this study demonstrated that new transmission sys- tems and the expansion of wind power in high wind locations would allow Canada to reduce the overall level of GHG emissions [145]. Ref. [145] focuses on supply options for meeting a fixed demand and the proposed model does not include DR programs assuming a perfectly inelastic electricity demand.

A review of co-optimization models for GEP (including distributed and VREs), TEP, traditional DSM programs (including DR) is addressed in [28], which also reviewed the main available co-optimization tools. Therefore, the integration between GEP and TEP models together with DR strategies to seek optimal expansion plans for the long-term under co-optimization approaches has also been proposed by recent research works. A source-grid-load coordinated optimization planning model is proposed by [150] using a MINLP model to seek a general optimal expansion solution for minimizing the overall power system costs, including the cost of DR employment and social costs for an IEEE 30-bus system case study. The regulation constraints are also included in the co-optimization model developed by [150]. Outcomes of the proposed model revealed that the inclusion of DR measures into the modellingapproach might provide a low-cost pathway for integrating wind energy resources in the power system. Also, the source-grid-load coordinated planning model might reduce the overall system costs. The computa-tional effort seems to largely increase when simultaneously taking supply and demand-side resources into account. A source-grid-load planning model has also been proposed by [151] focused on the Chi- nese power sector. In addition to the generation and transmission expansion planning, the model also considers the resources from thedemand-side. The inclusion of DSM into the modelling framework hasalso been proposed by Ref. [152], which proposed a model for the in- tegrated planning of generation and transmission expansion for the interconnected Colombian power system. The authors of [152] also concluded that reconfiguring the existing power generating technolo- gies would significantly reduce the CO_2 emissions in the country.Ref. [153] also included DR resources into their modelling framework for the generation and transmission expansion planning problem. Findings of [153] revealed DR as a valuable resource, which might change the location, economics but also the required investments in generation and transmission. A bi-level planning model is proposed by [154], addressing the simultaneous expansion of generation and trans- mission (GTEP) by also incorporating the DR effects. The upper-levelmodel addresses the GTEP problem whose output data is used in the lower level, simulating the system's operation during a peak load day in the target year.

Ref. [155] dealt with the generation-transmission co-optimization problem when a pay-as-bid auction was in place. In a further research study, Ref. [156] addressed whether or not risk aversion might affect the optimal transmission and generation expansion planning, whereas Ref. [35] proposed a generation-transmission expansion planning model for mitigating the power's system vulnerability to deliberate physicalattacks.

3.2.2. Co-optimization between electricity and gas networks

A comprehensive comparison among previous studies which deal with co-optimization between electricity and gas systems (also referred to as gas-electric expansion planning or even natural gas grid expansion planning – NGGEP) with a particular focus on the long-term is presented in Table A7 (Appendix A). The coordinated expansion planning for electricity and natural gas network infrastructures would allow the optimal management of RES towards low carbon pathways [48], but it might also support the identification of least-cost investment alterna-tives [157]. The authors of [48] highlighted the synergies between co-optimization between power and natural gas systems, including sus-tainability and reliability issues. A review of the modelling approaches from the joint planning of power and natural gas networks coordination is addressed in [48] focused on long-term planning aspects.

Ref. [158] included the natural gas infrastructure planning objective into the co-optimization model of both power generation and trans-mission planning. Along the same lines, Ref. [159] subsequently argued that although previous research works have addressed the co-optimization of electric power and natural gas infrastructures, the ma-jority of previous studies did not incorporate the response to extreme events into the modelling frameworks. A broader perspective has been adopted by Ref. [159], who developed a tri-level planner-disaster-risk-averse-planner framework suitable for resilience-oriented integrated planning considering electric power and natural gas networks with a particular focus on enhancing the system's resilience in response to extreme events.

A deterministic long-term expansion model which co-optimizes electricity and NG infrastructures was addressed by Ref. [157]. This last model accounted for planning the expected investments in new generation and transmission systems but also the required new pipelinesfor a 26-node integrated gas-electric system in the United States. A long- term generation and transmission expansion planning model is proposed by [160], taking into account the NG system acting under an imperfect competitive electricity market environment. The authors of Ref. [160] also called attention to the innovative aspects of their proposal since the expansion decisions are also based on a social perspective, including social welfare and consumer benefits.

Co-planning between electricity and NG networks has also been addressed by Ref. [161], taking into account the short (e.g., renewable energy production) and long-term (demand growth and gas price) un-certainties. The integration between electricity and NG networks at the distribution level has been addressed by [162] through a long-term planning model using a MINLP formulation. Co-optimization of power and natural gas systems for a hydro-based power system is investigated in the work of [163], taking the uncertainties related to water flow changes, demand fluctuation and the variability of intermittent renew-able generation into account. A long-term investment co-optimization model for natural gas and power systems is also proposed by [164], considering reliability concerns related to the interdependency between the electricity and NG networks.

Co-optimization expansion planning of natural gas and electricity transmission systems is addressed by Ref. [165] by simultaneously taking into account N-1 contingency in NG and electricity systems. Ref. [166] focused on a multi-vector energy system model for the interconnected systems of Ireland and Great Britain. The critical role developed by both PtG and gas storage for supporting the lack of gas has been pointed out by Ref. [167]. A co-expansion bi-level programming planning model is proposed by Ref. [37] for the integrated planning between electricity and NG networks (also including PtG technologies). The authors of [33] also integrated PtG technologies in a multi-stagecontingency-constrained co-optimization model for electricity-gas sys- tems integrated with gas-fired units. While most studies have focused on the co-optimization between electricity and natural gas networks, Ref. [168] focused on the co-planning between shale gas technology and the electricity network. The model proposed by [168] focused on providing helpful information regarding the trade-offs between system reliability and costs.

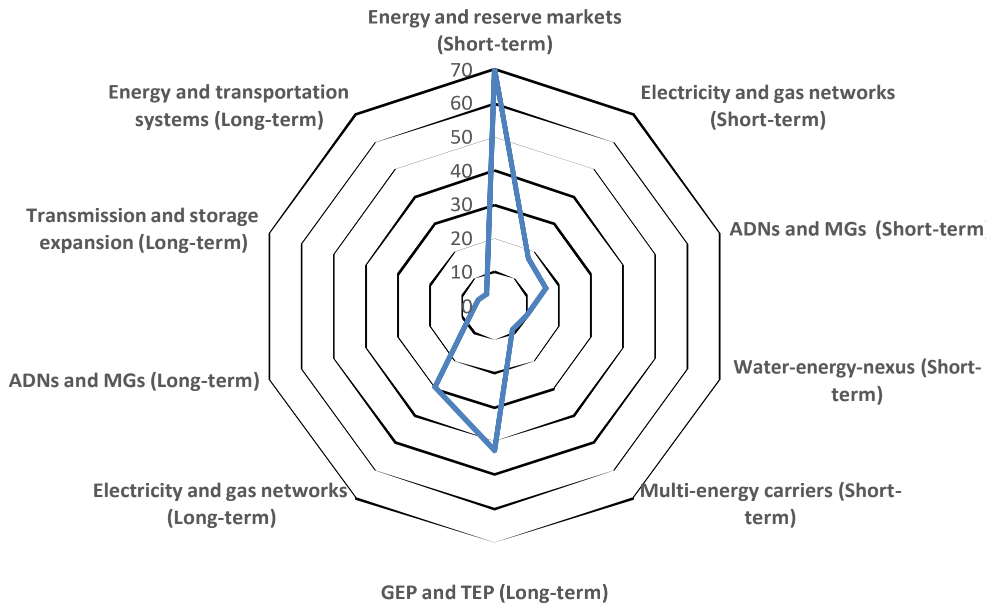

Fig. 3. Number of selected papers in each category (short and long-term).

3.2.3. *Co-optimization in active distribution networks (ADNs) and micro grids (MGs)*

The use of co-optimization approaches in Active Distribution Networks (ADNs) and Micro Grids (MGs) with a particular focus on the long-term has also been centre of previous research, such as illustrated in Table A8 (Appendix A). A co-optimization model for distributed energy resource planning focused on the optimal sizing of DERs in a MG envi- ronment has been addressed by [169] to minimize the annualized sys- tem costs and maximizing fuel savings. Further, a micro-grid-based co- optimization planning problem was investigated in [170] to minimize the total investment and operation costs of local MGs. The work of [170] proposed a micro-grid-based planning model as an alternative to the co-optimization of generation and transmission. A coordinated planning model for multiple MGs and distribution networks with flexible interconnections is addressed in the work of [171].

A two-stage co-optimization expansion planning model for active distribution systems is proposed by [172], considering multiple active network managements and evaluating the optimal load shedding direction. Later, the coupling between the distribution network's expansion planning with EVCSs was addressed by [173,174]. These last two papers, however, did not consider both BESS and the insertion of renewable-based DG. A further research work [175] improved these concerns by developing a multi-objective joint planning model for ADNs. The model proposed by [175] aimed to co-optimize the sizing and siting of multiple resources, including RES-based DG from wind and solar power, BESSs, distribution network expansion and EVCSs for the minimization of reliability and investments costs and at the same time maximizing the electric vehicle charging service capability.

3.2.4. *Co-optimization between transmission and storage expansion*

Previous research has also dealt with co-optimization between transmission network expansion planning and storage systems (see Table A9 – Appendix A). Overall, these research works highlight the economic benefits achieved by the storage expansion co-planning. A tri- level co-optimization model for transmission expansion planning coupled with storage siting and sizing is addressed in [176]. A long-term expansion planning model has been developed by Ref. [177], which simultaneously takes into account the network expansion and the BESS placement under a market-driven approach. The authors of [177] concluded that the expansion of transmission networks with batteries might be cost-effective, especially for market-driven electricity systems. Ref. [32] focused on a long-term stochastic multistage co-planning transmission expansion model and energy storage. The model con- siders possible delays in expanding the transmission network and the storage degradation along with the planning period. The optimal sizing and siting of ESS are performed in the work of [178] through a co- optimization model for transmission expansion planning and ESS. A novel two-stage stochastic programming model for the co-optimizationof transmission switching operations and storage investments (including siting and sizing ESS decisions) was further proposed by [179]. This last model also takes into account the maximum allowed limits for both load shedding and renewable curtailment.

3.2.5. *Co-optimization between energy and transportation systems*

Our literature review also found some particular research works focused on the co-planning between energy and transportation systems (Table A10 – Appendix A). A long-term investment planning model has been developed by [180] using the National Long-term Energy and Transportation Planning (NETPLAN) software focused on a 40-year planning period for both the United States energy and freight transportation systems. This research focused on identifying the possible benefits of building a national transmission overlay in the country. A further work [181] also employed NETPLAN to develop a long-term investment planning model that considers the co-optimization of en- ergy, freight and passenger transportation systems. The authors evalu- ated hydrogen integration into the NETPLAN model, which is used as an alternative for light-duty vehicle transportation in the United States. The NETPLAN software was also employed by [182] to co-optimize infrastructure investments and operations for the transportation and energy sectors in the United States. Findings of [182] revealed that both thecosts and CO_2 emissions are likely to decrease for significant high-speed rail diffusion scenarios. The NETPLAN software has also been employed to integrate biomass pathways across the energy and transportation sectors in the United States based on a 40-year multi-period co-optimi- zation model [183].

3.3. *Summary of the findings*

This section provides a summary and discussion regarding the main findings achieved from the systematic literature review. Overall, the use of co-optimization approaches to support short and long-term decision-making in the energy sector has been widely applied and discussed, addressing different facets of the problem, such as illustrated along with this review paper. The number of reviewed papers in each category is summarized in Fig. 3.

Short-term electricity planning is usually associated with day-ahead, intra-day and real-time markets and these models are well suited to deal with variability issues in power systems [184]. Co-optimization of energy and reserves in the day-ahead market has become a reality for many countries worldwide. The authors of [185] pointed out that the co-optimization of energy and reserve market "*produces lower bid-cost solutions than sequential procurement*". Thus, the practice of co-optimization for ancillary services purposes is an emerging field of research and might bring ancillary savings costs from 30 to 50%, according to the results from Ref. [186]. The Frequency Control Ancillary Services (FCAS) in the Australian electricity market, for instance, have been procured in conjunction with the energy market [187]. The co-optimization of energy and reserve resources is already implemented in most of the United States markets [60,188] but also in the Greek electricity market [189]. Ref. [188] highlights the considerable potential of using co-optimized approaches for energy and reserve markets within Europe, but the authors pointed out that implementing such approaches is not expected to occur in the short-term for the European territory.

Two widely used co-optimization approaches for energy and reserve markets include robust and stochastic co-optimization [85]. Robust optimization was used by [89,90,190], for example. Stochastic co-optimization approaches in the context of energy and reserve markets, however, have been more widely employed such as in [61,63,65,67,68,75,84,91,191,192]. Mixed-Integer Linear Programming (MILP) models seem to be the most widely programming tool employed to model the co-optimization in energy and reserve markets, although many recent research works have also employed nonlinear programming approaches. DC-Optimal Power Flow (DC-OPF) and AC-Optimal Power Flow (AC-OPF) models are also among the most commonly used methods for co-optimization in energy and reserve markets. Overall, there seems to be some evidence to indicate that the software General Algebraic Modelling System (GAMS) is the most used tool in this category, followed by MATLAB and PLEXOS[6]. Numerical examples have been employed mostly based on IEEE bus test systems, but it can also be seen an increasing focus on real-case systems – particularly for United States regions and to a lesser extent for the Central European countries. Overall, the reviewed studies seem to support the fundamental role developed by storage options in providingancillary services for power systems. The research findings also consistently point towards the importance of integrating power distribution and district heating networks.

The focus of recent research in water-energy nexus co-optimization has also been driven by climate change issues that might condition the availability of water resources and, therefore, constraining the operation of the power system [113]. The majority of water-energy nexus co-optimization models have been developed using nonlinear programming approaches and MATLAB seems to be the most used tool in this category.

The evolution of ADNs is intrinsically related to the development of the flexibility services provided by DERs, which also support the Active Network Management (ANM), whose importance has been considerably increasing in the past few years due to the high-penetration of intermittent renewable energy [193,194]. Recent works have addressed the energy management problem of ADNs for multiple MGs (see Ref. [195–197], for instance). The integration of MGs into ADNs has been increasing along with the past years, mainly because of the rapid development of DG systems [195]. However, new challenges have appeared, including the problem of how to manage the operations of multiple MGs with different self-interests effectively.

The co-optimization of multi-carrier energy resources may offer a set of advantages such as performance improvements and cost savings, for example [119], and it has been the focus of much research in the past few years, such as in [45,93,198]. However, these models usually present higher complexity associated with high computational times, which would depend on the extent to which the operational details are included or not in the modelling approach [34]. Reducing the model temporal accuracy and relaxing the operational constraints has also been employed to reduce the complexity of such co-optimization approaches [34].

Previous research works have widely addressed long-term optimization models considering several solutions and modelling approaches, objective functions, geographical scope, temporal resolution, and considering centralized and decentralized approaches. The authors of [199] underlined the importance of considering the short-term operation constraints and requirements for long-term planning models. One of the more significant findings to emerge from this study [199] is that the availability of storage resources might lower the total system costs. Ref. [200] further support the importance of representing short-term operation for long-term decisions, especially for storage technologies that might be used in both short (e.g., batteries) and long-term (e.g., hydro) planning. A framework was developed in [201], which accounts for the inclusion of both short and long-term storage constraints for a two-level proactive transmission expansion model. How increasing operating reserve requirements impact generation capacity investments has been addressed by [202] for a power system with high RES integration. Findings of [202] revealed that operating reserve requirements might represent considerable additional costs for integrating high shares of renewable generation. The complexity of optimization problems with the inclusion of VRE resources has been highlighted in the work of [29].

Although a considerable amount of literature has also been published on optimization and co-optimization models for planning purposes (i.e., focused on the long-term), such studies remain narrow in focus dealing purely with optimization approaches. These studies have been generally linked to GEP and TEP problems, although co-optimization approaches in this field have been at the centre of much attention in recent years. A state-of-the-art review is addressed by Ref. [138], which explored, in particular, how equilibrium[7] co-planning generation and transmission expansion models have been developed under a market-based environment. Although the terms "*co-optimization*" and "*co-planning*" have been used interchangeably by previous research to refer to the joint optimization of generation and transmission, Ref. [138] argues that the term "*co-planning*" might be more accurate for the co-planning problem in market-based environments. In contrast, the term "*co-optimization*" is best suited for centralized environments (i.e., vertically-integrated electricity markets) in which a single entity makes the investment decisions. Ref. [28] also called the attention especially for unbundled market structures in which different entities perform the expansion planning of transmission and generation. For this case, the "*simultaneous optimization*" between these two classes of investments will become a different co-optimization paradigm called "*anticipatory transmission planning*[8]" which requires an iterative approach until achieving coordination between generation and transmission planning.

As a rule, over the past decades, generation and transmission planning models had been addressed as independent problems mainly due to computational limitations. The majority of studies in generation-transmission co-optimization have been based on least costly ap-proaches. However, Ref. [203] highlighted the weaknesses of such least

[6] PLEXOS software allows the co-optimization of energy and reserves provisions [293] and it has been widely employed in the co-optimization of unit commitment (UC) and economic dispatch (EC) problems [294].

[7] Ref. [146] called the attention to the new category of planning tools referred as equilibrium models. It is important to highlight that for perfectly- competitive markets the solution found by optimization models should be equivalent to the ones obtained from equilibrium models [146].

[8] *"A proactive or anticipative transmission planner makes transmission investments taking into account the effect of these upgrades on generation investments*

and, ultimately, on total system cost or social welfare [146]*".*

cost approaches and proposed a benefit maximization methodology that allows planners to allocate the available resources optimally. The incorporation of stakeholders' equality preferences into the generation-transmission planning model has also been proposed in the methodology of Ref. [203]. The authors also highlight the advantages of their pro-posed modelling approach, particularly for assessing the possibility of rebuilding a power system to maximize social welfare once their pro- posal is highly commendable for rebuilding power systems after natural disasters.

Most co-optimizations models for planning purposes have been considered by governments and regulatory bodies at national levels. Over the past two decades, significant advances have been made to address co-optimization problems in the energy sector, taking into ac- count some essential operational details [28]. A typical example is the increasing use of bi-level optimization approaches for generation and transmission planning [154]. The majority of previous studies on generation-transmission co-optimization have applied MILP models. However, although MILP models have also been widely employed forgas-electric expansion planning, MINLP is becoming more widespread. Therefore, many challenges are associated with expansion planning problems because of their long-term, large-scale, and nonlinear nature. Ref. [204] addressed a review of GEP optimization problems with renewable energy integration with a particular focus on identifying the impact of smart grid technologies, the treatment of uncertainties and the increasing need for operational flexibility on GEP problems. In a comprehensive literature review of optimization models, Ref. [205] also identified four significant short-term operation issues that recent liter- ature has included into planning models: (i) integration of VRE; (ii) demand-response; (iii) interregional transmission, and (iv) energy storage.

The majority of previous planning studies focused on generation and transmission expansion models have been conducted to minimize the total system costs (i.e., based on least cost-based approaches) once avertically integrated approach is usually assumed to be responsible for the planning. However, a large and growing body of literature has also pointed out the need for future models to minimize not only financial costs but also environmental and social ones, for example. Ref. [206]points out that the use of co-optimization approaches for generation- transmission planning purposes might be more suited for vertically- integrated utilities, i.e., the same entity is responsible for both genera- tion and transmission resources planning. Notwithstanding, Ref. [31] highlights that generation-transmission co-optimization approaches may also be useful for unbundled environments since they can identify possible grid reinforcements that would support more optimal genera- tion investment decisions and consequently decrease the overall system costs. The studies that couple supply and demand-side planning issuesare an emerging field of research in recent years. The potential benefits of using co-optimization in generation and transmission planning models are also considered very important in the context of high inte- gration of renewables [28].

Lower curtailment and investment deferrals have been reported when co-optimization approaches are followed in generation-transmission expansion studies. Findings of the study proposed by [31] support the idea that the potential benefits from co-optimization planning approaches usually include lower overall power system costs. Specifically, the savings might occur due to better retirement decisions, savings of generation investment and operating costs and efficient integration of other resources such as storage technologies, DR measures and DERs. Ref. [31] found that the generation dispatch and investment might be affected with the inclusion of DSM strategies or storage tech- nologies into the co-optimization model. Therefore, co-optimization might result in significantly different patterns of investment than traditional planning strategies would suggest.

Co-optimization planning models for electricity planning and gas infrastructures have also been widely addressed by previous research. The joint planning between electricity and gas networks has been addressed by employing both single and multi-investment decision-making strategies. Many recent studies (such as Refs. [33,37,167]) have also shown the advantages of using PtG technologies in co-expansion planning models between gas and electricity systems. Possible barriersto the co-optimization between natural gas infrastructure and power system expansion still exist, particularly for markets where these sys- tems are planned independently and by different organizations [157].

Recent developments in the field of ADNs and MGs have led to a renewed interest in the use of co-optimization in these particular fields. Previous works have also addressed the co-optimization of multiple micro energy grids. Recent research has also focused on the co-optimization in multi-energy carriers, which might offer advantages such as performance improvements and cost savings. Recent research works have also addressed relevant applications focused on co- optimized solutions for island systems, usually to find the least-cost solutions. There has been substantial research dealing with the use of storage under co-optimization approaches, which includes BESS, PHES and CAES, for example. The optimal sizing and siting of energy storage systems in transmission systems has also been at center of recent research. Particular previous studies have also addressed the use of co- optimization focused on integrated energy systems (i.e., multi-energy carriers). Other recent studies also provided pathways related to the co-optimization of EVs applications, power and desalination plants, energy and comfort issues in buildings, just to name a few.

4. Conclusions

This study makes a significant contribution to research and fills a gap in the literature by demonstrating the role of co-optimization ap- proaches in both short and long-term resource operation and planning problems within the energy sector. This review found evidence that the use of co-optimization strategies has increased markedly over the last few years in both operational and planning models, although many terms have been used interchangeably to refer to co-optimized models. In the period investigated, short-term co-optimization of energy and reserve markets and long-term co-optimization of generation- transmission expansion planning have attracted the most attention from researchers. The study of power grid and gas networks applications has also increased significantly in the last years.

The main conclusions from this research can be then summarized as follows.

(1) The research findings reported here seem to be consistent with other research (see Ref. [207]), which indicates that co-optimization might provide the capability of lower investment and operating system costs. Overall, such approaches are likely to lead to less costly solutions than traditional optimization tech- niques. Our literature review revealed that different objective functions had been considered for the co-optimization, but, in general, the minimization of the total system costs is the most employed among the reviewed papers.

(2) Research has consistently shown that the use of co-optimization approaches can be technically challenging. Overall, a set of techniques such as relaxation, decomposition and linear ap- proaches have been proposed for reducing the inherent nonlinear model's complexities. Heuristic optimization strategies have also been employed to support the complex nature inherent to co-optimization approaches.

(3) It is shown evidence that the vast majority of studies on short- term co-optimization approaches have grown up around energy and reserve markets and the IEEE Reliability Test System (RTS) seems to be the most employed case-study among the reviewed studies. Co-optimizing day-ahead and balancing markets have been a particular identified trend among the reviewed research within short-term applications. The majority of studies on short-

term co-optimization focus on day-ahead scheduling and a lesser extent on real-time markets.

(4) Overall, long-term planning models significantly differ in terms of temporal resolution, geographical scope, technologies considered and regional disaggregation but also on the programming strategy and tool used to solve such co-optimization problems. In general, the great majority of previous co-optimization models between generation and transmission expansion planning do not use high temporal resolution due to computational limitations. Short-term operational constraints in long-term power planning models have also been addressed by recent research, which impacts investment decisions. Overall, the reviewed studies on GEPTEP expansion clearly indicate the importance of including short-term operation requirements and storage technologies within long-term planning models. A growing body of recent research addresses the problem of generation and transmission expansion planning considering the high integration of RES in multi-region power systems.

(5) The long-term co-optimization between generation and transmission is usually best suited for centralized vertically-integrated electricity markets [28,138]. However, the recent liberalizationof electricity markets raised the question regarding the usefulnessof such approaches since new dynamics have been introduced by this novel market model, which can lead to conflicting interests among stakeholders and decision-makers.

(6) Although most studies that tackle the integration between GEPand TEP models under co-optimization approaches have focused on generation and transmission integration only, a considerable amount of literature has been published on the joint planning of GEPTEP models with the presence of DERs. This finding corroborates with Ref. [72], which pointed out that the large-scale diffusion of DER "*requires a stronger integration of transmission and generation planning with the distribution networks, demanding several advances in the existing tools and methodologies*".

(7) Several ways have been used to relax MINLP formulation. MINLP models have been transformed to MILP in some cases, usually for problems of larger size that are computationally intensive. However, it can result in loss of model fidelity. The big question that arises is how to preserve a high level of fidelity when applied to real/practical systems, which usually comes with increased computational challenges in solving the co-optimization prob- lem. Therefore, there are a set of associated challenges between modelling fidelity, spatial granularity and geographical coverage and it remains a challenging research issue. The modelling of multiple sectors, for instance, might increase the computational efforts considerably. To address such problems, spatial aggregation and reduced temporal granularity have been employed [28]. In some cases, to increase the model's fidelity, integer variables and/or nonlinear variables are included in the optimization problem transforming the problem into a MILP, MINLP or NLP.

(8) Finally, we have identified that several models have also been proposed tackling the integration between the power grid and natural gas systems under co-optimized approaches. The integrated planning between electricity and gas networks is useful for both operational and long-term planning purposes. Therefore, the joint (or combined) planning of power systems and NG systems has been widely considered in the past years. The short-term co-planning between electricity and gas networks is particularly important since the peak demand for electricity and NG might be at different times. The advantages of co-planning between elec- tricity and gas networks come partially from the offered flexi-bility from natural gas to meet short-term supply and demands requirements once apart from power grids; gas might be stored in the pipelines. Previous studies on co-optimization between elec- trical and natural-gas systems with the power to gas technology (PtG) have also been widely acknowledged in the literature and it has been identified as a trend for future planning models.

The findings reported here should make an essential contribution to the energy field. The use of co-optimization was found to be very useful to address critical concerns in both short and long-term planning issues, but also evidence is presented showing that such approaches might be more effective in capturing the trade-offs between two or more sectors. The findings of this study have a number of practical implications since they provide essential contributions to international scientific knowl- edge and are expected to be a powerful tool to guide and support poli- cymakers and stakeholders in the sector, providing both integrated optimal investment strategies and possible revisions in policy design plans. The findings might suggest several courses of action for govern- ments and/or regulatory bodies to develop national and regional policy analysis. The governments might have a deeper understanding regarding the risks, benefits and costs of the available resource options, but they can also improve the decision-making process through inte- grated planning alternatives offered by co-optimization approaches. Although far from being exhaustive, our comprehensive literature re-view aimed to illustrate the diversity of approaches and models used by different research works and demonstrate their application potential to different operational and planning problems within the energy field.

5. Research gaps and prospects

This study provides a comprehensive review of existing research on the use of co-optimization in the energy sector. We attempted to identify recent progress in the field but also the challenges arising from the employment of such approaches. However, regardless of all the benefits associated with the use of co-optimization approaches, our literature review also revealed that due to the increasing complexities and trade- offs of the energy sector, a set of challenges for future co-optimization models include (i) dealing with the treatment of uncertainties and (ii) take into account the trade-offs among modelling fidelity, spatial gran- ularity and geographical coverage, which remains a challenging research issue. These findings are also in agreement with Ref. [208], which addressed the twenty-first-century energy challenges for energy systems models, and pointed out the need for future energy models to integrate human and social risks/opportunities. As such, co- optimization is revealed to be also a data-intensive procedure. The need to coordinate the necessary data from multiples actors might in- crease the problem's complexity since security and confidentiality issues would also be put on the table.

Considering the significant challenges faced by the energy sector coupled with the trade-offs between climate neutrality goals, there is abundant room for further progress in developing innovative mechanisms and market development schemes through the use of co-optimization approaches. This could significantly facilitate the integration of renewable energies and, under certain circumstances, considerably reduce the need for grid expansion. Future studies on the current topic are therefore recommended and include:

1. Although the importance of co-optimization approaches, little work has also been identified in the co-optimization of systems with a high share of RES and responsive loads. The development of co-optimization models for long-term decision-making to recognize the impact of short-term variability of both demand and RES supply and well-suited systems with a high share of RES and under different demand flexibility conditions is imperative. This is particularly important given the need to address climate change concerns but at the same time envisaging a "*just energy transition*".
2. The need for future models to address real-case systems since most studies have been applied to non-real networks, i.e., using theoretical test cases.

3. The inclusion of energy efficiency resources under co-optimization modelling approaches in both short and long-term models.
4. Co-optimization might also be employed to determine the optimal market share among electric, biofuels and flexible-fuel vehicles. The integration of EVs as flexible loads has also been at the centre ofmuch attention [209,210]. The co-optimization of battery size andenergy management focused on plug-in hybrid electric vehicles is addressed by Ref. [211]. A co-optimization model for fuel cell hybrid vehicles is investigated in [212], accounting for the interactions between design and control strategy. The EVs charging process has been used to provide frequency regulation in the model proposed by [213] using a case study based on the Central-Ohio region that co-optimized DER, including photovoltaic solar panels and battery energy storage.

This study also identified current research gaps in the field. There- fore, there are still many unanswered questions to be addressed in future studies, including: (i) To which extent may the use of co-optimization lower curtailment and promote investment deferrals? (long-term); (ii) How can we get advantages from the use of co-optimization in the era of unbundled market structures? (short- and long-term); (iii) How demand-side management strategies would affect the savings of generation and transmission capacity at the planning stage under the use of co-optimization? (long-term) and (iv) How to effectively manage the operations of multiple MGs with different self-interests? (short- and medium-term).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Literature review on the use of co-optimization in the energy sector.

See Table A1–A10.

Table A1
A literature review on short-term co-optimization between energy and reserve markets.

Ref.	Year	Sector(s)	Spatial Resolution	Planning Horizon	Objective	Programming/tool	Co-optimization explicitly mentioned?
[50]	2002	Power system	6-unit test system and 17-unit test system	Short-term (day-ahead)	Minimization of the total system cost	Linear Programming (LP) and Sequential Quadratic Programming (SQP)	No
[214]	2004	Power system	3-bus DC network	Short-term (day-ahead)	Minimization of the total system cost	AC Optimal Power Flow (AC-OPF)	No
[54]	2005	Power system	Modified IEEE 30-bus system	Short-term (real-time market)	Minimization of the total expected cost	*Augmented Optimal Power Flow (AOPF)*	Yes
[58]	2006	Power system	Power system with 26 generating units	Short-term (day-ahead for single period scheduling and 8-hours for multi-period scheduling)	Minimization of the total production cost	Mixed-Integer Programming (MIP)	Yes
[215]	2007	Power system	Western System Coordinating Council (WSCC) – 9-bus test system	Short-term (day-ahead)	Minimization of the total expected cost	n/a	Yes
[216]	2007	Power system	Power system with 6 generating units, 20 buses and 24 transmission lines	Short-term (day-ahead)	Minimization of the payments of energy and reserve offers	Dynamic Optimal Power Flow (DOPF)	Yes
[217]	2009	Power system	IEEE 24-bus system	Short-term (day-ahead)	Minimization of energy and reserves offer cost	Mixed-Integer Linear Programming (MILP)	No
[218]	2009	Power system	Roy Billinton Test System	Short-term (day-ahead)	Minimization of the total operating cost	Mixed-Integer Nonlinear Programming (MINLP)	Yes
[86]	2011	Power system	Historical market data from several U.S. electricity markets	Short-term (day-ahead)	Maximization of the net revenue	Mixed-Integer Linear Programming (MILP)	Yes
[91]	2011	Power system	IEEE 24-bus system	Short-term (day-ahead)	Minimization of the total cost of energy and reserve production	Mixed-Integer Linear Programming (MILP)	No
[190]	2011	Power system	10-unit system	Short-term (day-ahead)	Minimization of the expected total cost	Mixed-Integer Linear Programming (MILP)	No
[57]	2012	Power system	Two case studies (IEEE 6-bus and		24-bus		s y

			ems)	Short-term (day-ahead)	Minimization of the operating cost	Two-Stage Stochastic Mix-Integer Non-Linear Programming (TSSMINLP)	Yes
[88]	2012	Power system	Medium-scale real test system from Greece	Short-term (day-ahead)	Maximization of the power company profit	Mixed-Integer Linear Programming (MILP)	Yes
[191]	2012	Power system	IEEE RTS	Short-term (day-ahead)	Minimization of the total expected cost	Mixed-Integer Linear Programming (MILP)	Yes
[75]	2013	Power system	IEEE 118-bus test system	Short-term (day-ahead)	Maximization of the expected profit	Mixed Integer Programming (MIP)	Yes

(*continued on next page*)

Table A1 (*continued*)

Ref.	Year	Sector(s)	Spatial Resolution	Planning Horizon	Objective	Programming/tool	Co-optimization explicitly mentioned?
[55]	2013	Power system	IEEE 30-bus system and IEEE 118-bus system	Short-term (day-ahead)	Minimization of the expected cost	AC power flow formulation with static and dynamic security constraints	Yes
[56]	2014	Power system	Two case studies (4-bus and IEEE 30-bus systems)	Short-term (day-ahead)	Minimization of the total system cost.	Mixed-Integer Linear Programming (MILP)	Yes
[66]	2014	Power system	Several regions and storage technologies in the U.S.	Short-term (day-ahead and real-time markets)	Maximization of net revenue	Mixed-Integer Linear Programming (MILP)	Yes
[79]	2014	Power system	IEEE RTS	Short-term (day-ahead)	Minimization of the expected net cost	Mixed-Integer Linear Programming (MILP)	Yes
[219]	2015	Power system	IEEE 14-bus and 57-bus systems	Short-term (day-ahead)	Minimization of the operating cost	Stochastic Mix-Integer Nonlinear Programming (SMINLP)	Yes
[220]	2015	Power system	Central Western European (CWE) market	Short-term (day-ahead)	Minimization of the total generation costs	Mixed-Integer Linear Programming (MILP)	Yes
[221]	2015	Power system	IEEE RTS	Short-term (day-ahead)	Minimization of the expected cost	Linear two-stage mixed-integer stochastic optimization model	Yes
[81]	2015	Power system	Modified IEEE 30-bus system	Short-term (day-ahead)	Minimization of the expected total cost	Chance constrained optimization using YALMIP – MATLAB	No
[77]	2015	Power system	IEEE 24-bus test system	Short-term (day-ahead)	Minimization of the total production cost	Mixed-Integer Linear Programming (MILP)	Yes
[222]	2015	Power system	A test case that approximates the Texas electricity market	Short-term (one year – hourly)	Minimization of the total system cost	Mixed-Integer Programming (MIP)	Yes
[80]	2015	Power system	3-bus system and IEEE 24-bus RTS	Single period	Minimization of the total system cost	Mixed-Integer Linear Programming (MILP)	Yes
[74]	2015	Power system	IEEE 24-bus RTS	Short-term (day-ahead)	Minimization of the total operating cost	Robust optimization model	Yes
[76]	2016	Power system	CSP power plant – 110 MWe	Short-term (day-ahead)	Maximization of the profit	Mixed-Integer Linear Programming (MILP)	No
[78]	2016	Power system	New York Independent System Operator (NYISO) market	Short-term (day-ahead)	Maximization of the profit	Linear programming	Yes
[223]	2016	Power system	IEEE 118-bus test system	Short-term (day-ahead, 4-hour-ahead and real-time markets)	Minimization of the total production cost	Mixed-Integer Linear Programming (MILP)	Yes
[63]	2016	Power system	Hydropower company from the Spanish electricity market	Short-term (day-ahead)	Maximization of the expected profit of a hydropower producer	Mixed-Integer Linear Programming (MILP)	Yes
[224]	2016	Power system	20-kV MG	Short-term (day-ahead)	Minimization of the operating cost and emissions	AC Optimal Power Flow (AC-OPF)	Yes
[64]	2016	Power system	Two case studies (hydrothermal scheduling)	Short-term (day-ahead — 4 h step)	Minimization of the expected total cost	Mixed-Integer Linear Programming (MILP)	Yes
[225]	2016	Power system	Two illustrative case studies.	Short-term (day-ahead)	Maximization of the expected social welfare	Direct Current Optimal Power Flow (DC-OPF)	Yes
[226]	2017	Power system	Modified IEEE 118-bus system	Short-term (day-ahead)	Minimization of the total system cost	Mixed-Integer Quadratic Programming (MIQP)	Yes
[227]	2017	Power system	IEEE-30 bus test system	Short-term (day-ahead)	Maximization of the social welfare	Optimal Power Flow (OPF)	Yes
[228]	2017	Power system	Real MG with various DERs	Short-term (day-ahead)	Maximation of the total revenue from the energy, spinning reserve and flexible ramping products markets	Robust Mixed-Integer Linear Programming (RMILP)	Yes

[229]	2017	Power system	Numerical examples (based on China 2050 RES scenarios)	Single-level problem	Maximation of the participant's profits	MiXed-Integer Quadratically Constrained Programming (MIQCP)	Yes
[230]	2017	Power system	IEEE 30-bus system with two wind-farms	Short-term (day-ahead)	Minimization of the total operating cost	Optimal power flow (OPF)	Yes
[87]	2017	Power system	Test system: 1 Wind power plant; 5 thermal units and 1 pumped-hydro storage system	Short-term (day-ahead)	Maximization of the total expected profits from the producer	MiXed-Integer Linear Programming (MILP)	Yes
[52]	2018	Power system	Five power systems (which can be interconnected)	Short-term (day-ahead)	Minimization of the total daily cost	MiXed-Integer Linear Programming (MILP)	Yes
[231]	2018	Power system	8-zone new England test system	Short-term (day-ahead)	Maximization of the expected lifetime profit of the energy storage units	MiXed-Integer Linear Programming (MILP)	Yes

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Table A1 (*continued*)

Ref.	Year	Sector(s)	Spatial Resolution	Planning Horizon	Objective	Programming/tool	Co-optimization explicitly mentioned?
[69]	2018	Power system	Two MGs	Short-term (half-hourly simulations for representative days for different seasons)	Minimization of the expected total cost	MiXed-Integer Linear Programming (MILP)	Yes
[188]	2018	Power system	Central Europe	Short-term (day-ahead)			
					Minimisation of total electricity generation costs	Linear programming	Yes
[92]	2018	Power system	IEEE RTS – Four case studies	Short-term (day-ahead)			
[53]	2018	Power system	Case-study of the Greek power system	Short-term (day-ahead – 8 days)	Maximization of the social welfare	MiXed-Integer Programming (MIP)	Yes
[70]	2019	Power system	MG with 12 dispatchable DGs	Short-term (day-ahead)	Minimization of the total daily cost	MiXed-Integer Linear Programming (MILP)	Yes
[67]	2019	Power system	A case study with 1000 prosumers	Short-term (day-ahead)	Minimization of the expected total cost	MiXed-Integer Linear Programming (MILP)	Yes
[84]	2019	Power system	An isolated power system of Lanzarote-Fuerteventura	Short-term (day-ahead)	Minimization of the cost of the aggregator	A two-stage stochastic optimization model	Yes
					Minimization of the total operating cost	MiXed-Integer Linear Programming (MILP)	Yes
[65]	2019	Power system	MG with 3 feeders	Short-term (day-ahead)	Maximization of the profit from the MG	MiXed-Integer Nonlinear Programming (MINLP)	No
[62]	2019	Power system	IEEE RTS	Short-term (day-ahead)	Minimization of the energy dispatch cost	MiXed-Integer Linear Programming (MILP)	Yes
[82]	2019	Power and gas networks	IEEE 24-bus RTS and a 10-node gas network	Short-term (day-ahead and real-time markets)	Minimization of the cost of power system operation	MiXed-Integer Non-Linear Programming (MINLP)	Yes
[232]	2019	Power system	IEEE 24-bus test system	Short-term (day-ahead)	Minimization of the expected total cost	Stochastic programming	Yes
[233]	2020	Power system	Modified IEEE Reliability Test System (RTS) — 24-bus system	Short-term (day-ahead)	Minimization of the total daily cost	DC-Optimal Power Flow (DCOPF)	Yes
[61]	2020	Power system	6-bus system	Short-term (day-ahead)	Maximization of the expected profit	MiXed-Integer Linear Programming (MILP)	No
[234]	2020	Power system	6-bus and IEEE 118-bus test systems	Short-term (day-ahead)	Minimization of the expected total cost	MiXed-Integer Linear Programming (MILP)	No
[235]	2020	Power system	6-bus and a modified IEEE 118-bus systems	Short-term (day-ahead)	Minimization of the weighted sum of costs of all scenarios	Stochastic programming	Yes
[236]	2020	Power system	Modified IEEE 14-bus system	Short-term (day-ahead)	Minimization of the energy generation costs	MiXed-Integer Nonlinear Programming (MINLP)	Yes
[68]	2020	Power system	15-bus test system and 40-bus real network (MGs)	Short-term (day-ahead)	Minimization of the expected total cost	A two-stage stochastic optimization approach	No
[89]	2020	Power and district heating (distribution networks)	Barry Island system (9-bus power grid and a 32-node district heating network)	Short-term (day-ahead)	Minimization of the sum of energy and reserve dispatch costs of CHP units	Robust optimization -Linearized DistFlow branch model	Yes
[90]	2020	Power and district heating	Distributed system (6-bus power grid system and 4-node district heating network)	Short-term (day-ahead and real-time markets)	Minimization of the total system cost	MiXed-Integer Linear Programming (MILP)	Yes
[85]	2020	Power system	Large-scale hybrid AC/DC transmission grid	Short-term (day-ahead)	Minimization of the total generation cost	MiXed-Integer Linear Programming (MILP)	No
[83]	2020	Power and gas networks	IEEE RTS and 6-node natural gas system	Short-term (day-ahead)	Minimization of the total operation cost	Improved Alternating Direction Method of Multipliers (ADMM)	Yes
[237]	2020	Power system	PJM interconnection (largest system operator in North America)	Short-term (day-ahead)	Maximization of the social welfare	MiXed-Integer Linear Programming (MILP)	Yes
[238]	2020	Power system	Romanian power system	Short-term (day-ahead)	Minimization of the total operating cost	MiXed-Integer Linear Programming (MILP)	Yes
[239]	2020	Power and	Test system with three integrated	Short-term (day-ahead)			

		district heating	electricity and heating systems		Minimization of the total operating cost	Robust optimization	Yes
[240]	2020	Power system	An industrial consumer in New Zealand	Short-term (monthly – half-hour periods)	Minimization of the expected total cost	Mixed-Integer Program (MIP)	Yes
[241]	2020	Power system	Two case studies	Short-term (day-ahead)	Maximization of the expected profit and minimization of the expected emissions	Mixed-Integer Program (MIP)	Yes
[242]	2020	Power system	Central Western European system	Short-term (day-ahead)	Minimization of the total operating cost	Mixed-Integer Linear Programming (MILP)	Yes
[243]	2020	Power system	3-bus system and IEEE 30-bus system	Short-term (day-ahead)	Minimization of the total operating cost	Optimal Power Flow (OPF)	Yes

Table A2
A literature review on short-term co-optimization between electricity and gas networks.

Ref.	Year	Sector(s)	Spatial Resolution	Planning Horizon	Objective	Programming/tool	Co-optimization explicitly mentioned?
[98]	2008	Power and natural gas networks	Great Britain (GB) gas and electricity network	Short-term (31 days -daily time step)	Minimization of the combined operational costs (gas supplies, storage operation, power generation, and load shedding)	Non-linear programming	No
[97]	2011	Power and gas networks	Modified IEEE 118-bus power system and interstate natural gas pipelines	Short-term (day-ahead)	Minimization of the total operating costs	Mixed-Integer Nonlinear Programming (MINLP)	No
[93]	2015	Power and gas networks	Generation company	Multiple time horizons	Minimization of the total costs	Mixed-integer Programming (MIP)	Yes
[96]	2016	Power and gas networks	Regional (Illinois system)	Short-term (day-ahead)	Minimization of the negative social welfare (power grid) and minimization of the total compression cost (natural gas side)	Non-linear programming	Yes
[244]	2017	Power and gas networks	Two case studies (6-bus power system with a 7-node gas system and a modified IEEE 118-bus system with a 14-node gas system)	Short-term (day-ahead)	Minimization of the total costs	Mixed-Integer Nonlinear Programming (MINLP)	Yes
[99]	2018	Power and gas networks	Two case studies (6-bus power system with a 7-node NG system and a modified IEEE 118-bus power system with a 12-node NG system)	Short-term (day-ahead)	Minimization of the total costs	Mixed-Integer Linear Programming (MILP)	Yes
[46]	2019	Power and gas networks	Modified IEEE 24-bus power system with a 10-node NG system	Short-term (day-ahead)	Minimization of the expected operation cost	Mixed-Integer Linear Programming (MILP)	Yes
[245]	2019	Power and gas networks	Modified 24-bus IEEE RTS with a 12-NG system	Short-term (day-ahead and real-time)	Minimization of the total expected cost	Mixed-Integer Linear Programming (MILP)	Yes
[246]	2019	Power and gas networks	IEEE-30 bus power system with a 15-node natural gas network	Short-term (day-ahead)	Minimization of the expected operation costs	Nonlinear co-optimization	Yes
[95]	2020	Power and gas networks	District integrated natural gas and power system (IEEE 33-bus distributed system)	Short-term (day-ahead)	Minimize the total costs	Mixed-Integer Linear Programming (MILP)	Yes
[101]	2020	Power and gas networks	6-bus power system with a 6-node gas system	Short-term (day-ahead)	Minimization of the total operating costs	Mixed-Integer Nonlinear Programming (MINLP)	Yes
[247]	2020	Power and gas networks	IEEE 24-bus power system with a 12-node gas network	Short-term (day-ahead)	Minimization of the total costs	Mixed-Integer Linear Programming (MILP)	Yes
[248]	2020	Power and gas networks	IEEE 24-bus RTS system with a 12-node NG system	Short-term (day-ahead)	Minimization of the total expected system cost	Mixed-Integer Linear Programming (MILP)	Yes
[100]	2020	Power and gas networks	A system with an ESS, P2G device and a gas-fired generator	Short-term (day-ahead)	Minimization of the total costs	Mixed-Integer Linear Programming (MILP)	No
[94]	2020	Power and gas networks	IEEE 24-bus RTS system with a 10-node natural gas system	Short-term (day-ahead)	Minimization of the expected operation costs	Mixed-Integer Nonlinear Programming (MINLP)	Yes
[249]	2020	Power and gas networks	IEEE 24-bus reliability test system with a 12-node gas network	Short-term (day-ahead)	Minimization of the total costs	Second-order cone program	Yes
[250]	2020	Power and gas networks	Two case studies (6-bus power system with a 7-node NG network and IEEE RTS 24-bus system with the Belgian NG network).	Short-term (day-ahead)	Minimization of the total costs	Mixed-Integer Nonlinear Programming (MINLP)	Yes

Table A3
A literature review on short-term co-optimization of Active Distribution Networks (ADNs) and Micro Grids (MGs) between energy and reserve markets.

Ref.	Year	Sector(s)	Spatial Resolution	Planning Horizon	Objective	Programming/tool	Co-optimization explicitly mentioned?
[104]	2015	Power system (MGs)	Two systems (main grid and MG)	Short-term (day-ahead)	Minimization of the operating costs for the main and the MG	Mixed-Integer Linear Programming (MILP)	Yes
[105]	2016	Power system (electrical and thermal resources) (MGs)	Large university campus (California)	Short-term (1-hour resolution)	Minimization of the total operating costs	Mixed-Integer Linear Programming (MILP)	Yes
[251]	2017	Power system, cooling/heating and hydrogen (MGs)	Stand-alone MG	Short-term (1 year, 1-h resolution)	Minimization of the total costs	Mixed-Integer Linear Programming (MILP)	Yes
[252]	2017	Power system (MGs)	Stand-alone MG	Short-term (1 year, 1-h resolution)	Minimization of the total costs	Mixed-Integer Linear Programming (MILP)	Yes
[253]	2017	Power system (MGs)	MG with different generation and consumer units	Short-term (day-ahead)	Minimization of the total system cost	Mixed-Integer Linear Programming (MILP)	Yes
[103]	2017	Power system (MGs)	MG with three generating units and one ESS	Short (24 h) and long-term (6-year)	Minimization of the planning cost (long-term) and operational costs (short-term)	Mixed-Integer Nonlinear Programming (MINLP)	No
[254]	2018	Power system (MGs)	Existing off-grid mining operation (Québec, Canada)	Short-term (hourly)	Minimization of the annualized investment cost in DERs	Mixed-Integer Linear Programming (MILP)	Yes
[109]	2018	Power system (ADNs)	Modified IEEE 33-node distribution network	Short-term (hourly – 1 year)	Minimization of the ADN operation cost and Distributed Energy Storage System (DESS) investment cost	Mixed-Integer Second-Order-Cone Programming (MISOCP)	Yes
[108]	2018	Power system (ADNs)	Distribution system	Short-term (two typical days)	Minimization of the total losses or maximization of the total DG, EV charging station and ESS penetration or a multi-objective problem	Second-Order-Cone Programming	Yes
[110]	2018	Power system (ADNs)	Modified IEEE 34 and 123-bus distribution test systems	Short-term (30 min time-step)	Minimization of the repairing time and maximization of the picked-up loads	Mixed-Integer Linear Programming (MILP)	Yes
[102]	2018	Hybrid gas/ electricity/heat network (MGs)	Modified 13-bus and IEEE 30-bus power system, 20-node gas system and 14-node heating network	Short-term (24 h)	Minimization of load shedding and minimization of the total investment costs	Mixed-Integer Linear Programming (MILP) and Genetic Algorithm	Yes
[107]	2019	Power system (MGs)	Modified 18-bus and IEEE 33-bus test system	Short-term (24 h)	Minimization of the total costs	Mixed-Integer Nonlinear Programming (MINLP)	Yes
[106]	2020	Power system and natural gas (MGs)	IEEE 37-bus distributed system and 8-node natural gas system (Shenzhen park – China)	Short-term (day-ahead (capacity reconfiguration); Intra-day (energy dispatching) and real-time (reserve balance)	Minimum loss load rate (1st level); Maximum comprehensive benefit (2nd level) and Minimum reserve cost (3rd level)	Heuristic algorithms (chaotic ant colony algorithm)	Yes
[44]	2020	Power system (MGs)	MG with four thermal units and one hydrogen energy storage system	Short-term (day-ahead)	Maximization of the profits of consumers and MG operator	Robust optimization	Yes
[111]	2020	Power system (ADNs)	33-bus and a 136-bus system	Short-term (24 h)	Maximization of social welfare	Quadratic Programming (QP)	Yes
[255]	2020	Power system (ADNs)	Real distribution network (Zhejiang Province, China)	Short-term (24 h – 4 seasons in a year)	Three-level co-optimization	YALMIP toolbox	Yes

Table A4
A literature review on short-term co-optimization in water-energy-nexus.

Ref.	Year	Sector(s)	Spatial Resolution	Planning Horizon	Objective	Programming/tool	Co-optimization explicitly mentioned?
[116]	2014	Water-energy-nexus	Four power plants, three co-production desalination facilities and one reverse osmosis water plant	Short-term (day-ahead)	Minimization of the production costs	Nonlinear optimization model	Yes
[117]	2014	Water-energy-nexus	Three case studies	Short-term (real-time economic dispatch)	Minimization of the production cost	Nonlinear optimization model	Yes
[113]	2017	Water-energy-nexus	Greek power system	Short-term (one year with hourly time steps)	Minimization of the total operating cost	Mixed-Integer Linear Programming (MILP)	Yes
[115]	2017	Water-energy-nexus	Multi-stage flash (MSF) desalination plants	Short-term (day-ahead)	Minimization of the produced quantities of power and water	Mixed-integer quadratic constrained program	Yes
[256]	2018	Water-energy-nexus	Isolated freshwater and electricity production system	Short-term (one year with a time-step of 1/6 h)	Minimization of the embodied energy, Loss of electric Power Supply Probability and Loss of hydraulic Power Supply Probability	Genetic algorithm (NSGA-II)	Yes
[257]	2018	Water-energy-nexus	Topical case-study system	Short-term (day-ahead)	Maximization of the electric energy output	A *meta*-heuristic evolutionary optimization algorithm	Yes
[114]	2019	Water-energy-nexus	Scenario-based case studies (Greater Accra Metropolitan Area in Ghana	Short-term (day-ahead)	Minimization of multi-objective (CAPEX, OPEX and GHG emissions)	Mixed-Integer Linear Programming (MILP)	Yes
[258]	2020	Water-energy-nexus	Water-energy MG	Short-term (day-ahead)	Minimization of the operating cost of the water-energy MG	Mixed-Integer Nonlinear Programming (MINLP)	No
[118]	2020	Water-energy-nexus	Water-energy MG	Short-term (day-ahead)	Minimization of the daily cost of energy in the water-energy MG	Mixed-Integer Linear Programming (MILP) and Mixed-Integer Nonlinear Programming (MINLP)	Yes
[112]	2020	Water-energy-nexus	Micro water-energy system	Short-term (day-ahead)	Maximization of the overall cost of the micro water-energy system	Mixed-Integer Nonlinear Programming (MINLP)	Yes

Table A5
A literature review on short-term co-optimization in multi-energy carriers.

Ref.	Year	Sector(s)	Spatial Resolution	Planning horizon	Objective	Programming/tool	Co-optimization explicitly mentioned?
[45]	2007	Electricity, gas, and district heating systems	Hybrid energy hub	n/a	Minimization of the total energy costs	Non-linear optimization problem	Yes
[125]	2015	Integrated heat and electricity system	Four case studies	Day-ahead	Minimizing cost and the emissions from thermal units	Deterministic Non-Linear programming	Yes
[122]	2017	Electricity-heating-gas system	Two case studies (System 1: 6-bus power system, 7-node gas system and 4-node heat system and System 2: 39-bus power system, 20-node gas system and 8-node heat system)	Day-ahead	Three objective functions	Mixed-Integer Linear Programming (MILP)	Yes
[124]	2018	Integrated heat and electricity system	Representative heat-electricity system	Day-ahead	Minimization of the total energy cost	Mixed-Integer Conic Programming (MICP)	Yes
[123]	2019	Integrated heat and electricity system with heat storage	Model of the city of Aarhus (Denmark)	1-year	Minimization of the total annual investment and operational cost	Linear programming	Yes
[120]	2019	Electricity-heating-gas system	Islanded integrated energy system (8-bus electricity system, 9-node heating system and 8-node natural gas system)	Day-ahead	Minimization of the operation costs	Heuristic particle swarm optimization	Yes
[198]	2020	Gas, power, heating, and water energy sources with different energy storage technologies	6-bus power system with a 6-node gas network, and water and heat nodes	Day-ahead	Minimization of the operational costs	Mixed-Integer Nonlinear Programming (MINLP)	Yes
[121]	2020	Electricity-heating-gas system	Integrated energy system (modified 6-bus electricity system, 30-node heating system and 6-node natural gas system)	Day-ahead	Minimization of the operation costs	Mixed-Integer Nonlinear Programming	No
[259]	2020	Electricity-heating-gas system	IEEE 24-bus reliability test system, 12-node gas network and a 3-node district heating	Day-ahead	Minimization of the operational costs	Mixed-Integer Second-Order Cone	Yes

Table A4

(MINLP)

Table A6
A literature review on long-term co-optimization of generation-transmission expansion.

Ref.	Year	Sector (s)	Spatial Resolution	Planning horizon	Objective	Programming/tool	Co-optimization explicitly mentioned?
[143]	2010	Power sector	Chilean power system	Planning for 2030	Minimization of the total system costs	Mixed-Integer Linear Programming (MILP)	Yes
[260]	2010	Power sector	Portuguese power system	10-year planning horizon	n/a	Optimal Power Flow (OPF)	Yes
[261]	2012	Power sector	Multi-area power system	20-year planning horizon	Minimization of the total system costs	Mixed-Integer Programming (MIP)	No
[262]	2013	Power sector	Chilean power system	A single period (one-year horizon)	Minimization of the total system costs	Mixed-Integer Linear Programming (MILP)	No
[127]	2014	Power sector	Modified 6-bus test system and IEEE 24-bus RTS	Static (single period)	Minimization of the total system costs	Mixed-Integer Linear Programming (MILP)	No
[29]	2015	Power sector	Power system with solar PV, onshore wind and natural gas	Half-year planning period	Load-matching procedure and cost-minimizing techniques	Linear programming	No
[263]	2015	Power sector	Garver's six-bus system and IEEE 30-bus system	10-year planning horizon	Minimization of the total system costs	Bender's Decomposition	No
[141]	2015	Power sector	6-bus test system and IEEE 30-bus system	20-year planning horizon	Minimization of the total system costs	Mixed-Integer Nonlinear Programming (MINLP) and Mixed-Integer Linear Programming (MILP)	No
[264]	2015	Power sector	4-bus and 7-bus test system, and a modified IEEE 30-bus and 118-bus test system	Static (single period)	Minimization of the total system costs	Mixed-Integer Linear Programming (MILP)	Yes
[265]	2015	Power sector	240-bus network	50-year planning horizon	Minimization of the total system costs	Mixed-Integer Linear Programming (MILP)	Yes
[147]	2015	Power sector	Association of East Asian Nations region	Planning for 2050	Minimization of the total system costs	Linear programming	Yes
[153]	2016	Power sector	European electricity market (33 countries)	Static and multi-year representation	Maximization of total market surplus	Successive linear programming	Yes
[154]	2016	Power sector	IEEE 30-bus system	10-year planning horizon	Minimization of the total system costs	Mixed-Integer Nonlinear Programming (MINLP)	No
[146]	2016	Power sector	IEEE 24-bus RTS system	n/a	Minimization of the total system costs	Mixed-Integer Linear Programming (MILP)	Yes
[152]	2016	Power sector	Colombian power system	15-year planning horizon	Minimization of the total system costs	Mixed-Integer Linear Programming (MILP)	No
[126]	2016	Power sector	U.S. Eastern Interconnection system	16-year planning horizon	Minimization of the total system costs	Mixed-Integer Programming (MIP)	Yes
[150]	2016	Power sector	IEEE 30-bus system	5-year planning horizon	Minimization of the total system costs	Mixed-Integer Nonlinear Programming (MINLP)	No
[151]	2017	Power sector	Chinese power system	15-year planning horizon	Minimization of the total system costs	Mixed-Integer Nonlinear Programming (MINLP)	No
[139]	2017	Power sector	3-node system and modified IEEE 24-bus RTS system	Single-level problem	Minimization of the total system costs	Mixed-Integer Linear Programming (MILP)	Yes
[266]	2017	Power sector	5-bus test system, IEEE 118-bus test system and Chilean power system	Static (single period)	Minimization of the total system costs	Mixed-Integer Linear Programming (MILP)	Yes
[267]	2017	Power sector	3-bus and 6-bus test systems and modified IEEE 96-bus and 118-bus test systems	Static (single period)	Minimization of the total social costs	Mixed-integer bilevel linear program (MIBLP)	No
[137]	2017	Power sector	Case study of the U.S. Eastern interconnection	20-year planning horizon	Minimization of the total system costs	Mixed-Integer Linear Programming (MILP)	Yes
[156]	2017	Power sector	WECC 240-bus system	Static (single period)	Minimization of the weighted average of expected transmission and generation costs and their conditional value at risk (CVaR)	Stochastic programming	Yes

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[35]	2018	Power sector	IEEE 24-bus RTS	Static model (monthly)	Minimization of the total system costs	Mixed-Integer Linear Programming (MILP)	No
[268]	2018	Power sector	IEEE 118-bus test system	Static (single period)	Minimization of the total system costs	Mixed-Integer Nonlinear Programming (MINLP)	No
[36]	2018	Power sector	Australian National Electricity Market	12-year planning horizon (hourly resolution)	Minimization of the total system costs	Genetic algorithm (GA)	Yes
[269]	2018	Power sector	Case of Queensland (Australia)	14-year planning horizon	Minimization of the expected cost	Mixed-Integer Linear Programming (MILP)	Yes
[270]	2018	Power sector	Two cases (Garver IEEE system and IEEE 118-bus system)	25-year planning horizon	Three-level problem (i.e. with 3 objectives)	Mixed-Integer Linear Programming (MILP)	No
[155]	2018	Power sector	IEEE 24-bus test case	20-year planning horizon	Minimization of the total social costs	Non-linear model	Yes
[145]	2018	Power sector	Canadian power sector	Static (single period)	Minimization of the total system costs	Linear programming	Yes
[271]	2019	Power sector	IEEE 24-bus RTS and IEEE 118-bus test systems	15-year planning horizon	Minimization of the total system costs	Mixed-Integer Linear Programming (MILP)	No

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Table A6 (*continued*)

Ref.	Year	Sector (s)	Spatial Resolution	Planning horizon	Objective	Programming/tool	Co-optimization explicitly mentioned?
[132]	2019	Power sector	312-bus network representing the U.S. Western interconnection	50-year planning horizon	Minimization of the total system costs	Mixed-Integer Programming (MIP)	Yes
[272]	2019	Power sector	Regional Energy Deployment System (ReEDS) model (U.S.)	Planning for 2050	Minimization of the total system costs	Linear programming	Yes
[134]	2019	Power sector	IEEE 24-bus test system	10-year planning horizon	Minimization of the total system costs	DC-optimal power flow	Yes
[144]	2019	Power sector	Chinese power system	38-year planning horizon	Minimization of the total system costs	Linear programming	Yes
[148]	2019	Power sector	German power system	Planning for 2030 and 2050	Minimization of the total system costs	Linear programming	Yes
[149]	2019	Power sector	28 countries of the European Union	Planning for 2050	Minimization of the total system costs	Linear programming	Yes
[203]	2020	Power sector	Case study of Liberia (sub-Saharan Africa)	n/a	Benefit maximization approach (maximize the stakeholder's utility)	Mixed-Integer Linear Programming (MILP)	Yes
[140]	2020	Power sector	13 U.S. regions	34-year planning horizon	Minimization of the total system costs	Linear optimization	No
[142]	2020	Power sector	6-bus test and IEEE 118-bus system	10-year planning horizon	Minimization of the total system costs	Mixed-Integer Linear Programming (MILP)	Yes
[136]	2020	Power sector	169-bus system (representing the North American power grid	20-year planning horizon	Minimization of the total system costs	Linear programming	Yes
[273]	2020	Power sector	CAISO 17-bus data set	10-year planning horizon	Minimization of the total system costs	Mixed-Integer Nonlinear Programming (MINLP)	Yes
[274]	2021	Power sector	European power system	1-year planning horizon	Minimization of the total annual system costs	Linear programming	Yes

Table A7
A literature review on long-term co-optimization between electricity and gas networks.

Ref.	Year	Sector(s)	Spatial Resolution	Planning Horizon	Objective	Programming/tool	Co-optimization explicitly mentioned?
[275]	2010	Power and natural gas networks	Simplified Brazilian integrated gas and electricity system	11-year planning horizon	Minimization of the investment and operational costs	Mixed-Integer Linear Programming (MILP)	No
[276]	2013	Power and natural gas networks (at distribution level)	14-bus electricity system and 20-node gas network	10-year planning horizon	Minimization of the investment and operational costs	Mixed-Integer Nonlinear Programming (MINLP)	No
[277]	2014	Power and natural gas networks	Great Britain	25-year planning horizon	Minimization of both investment and operational costs	Mixed-Integer Linear Programming (MILP)	No
[278]	2015	Power and natural gas networks	Iranian power and NG system	3 and 6 years planning horizon	Minimization of the total costs	Mixed-Integer Nonlinear Programming (MINLP)	No
[158]	2015	Power and natural gas networks	Modified IEEE 118-bus system with a 14-node natural gas system	20-year planning horizon	Minimization of the interdependent electricity and natural gas infrastructures	Mixed-Integer Linear Programming (MILP)	Yes
[168]	2015	Power and shale gas networks	IEEE 24-bus RTS and a 12-node gas system	1-year planning horizon	Minimization of the investment costs	Mixed-Integer Nonlinear Programming (MINLP)	Yes
[40]	2015	Power and natural gas networks	Simplified Victorian gas and electricity networks (Australia)	1-year planning horizon	Maximization of the cost/benefit ratio	Mixed-Integer Nonlinear Programming (MINLP)	Yes
[279]	2015	Power and natural gas networks	IEEE 14-bus and a test gas system	12-year planning horizon	Maximization of the net present value (NPV) of the social welfare	Mixed-Integer Nonlinear Programming (MINLP)	Yes
[280]	2016	Power and shale gas networks	IEEE 24-bus electricity and 15-node NG system (China)	1-year planning horizon	Minimization of both investment and production costs	Mixed-Integer Linear Programming (MILP)	No
[281]	2016	Power and natural gas networks	Two systems (6-bus power system with a 7-node gas system and a modified IEEE 118-bus system with a	10-year planning horizon	Minimization of the investment and operational costs	Linear programming	Yes
[282]	2017	Power and natural gas networks	Modified IEEE-RTS 1979 system and a 17-node gas system	6-year planning horizon	Minimization of the investment and operational	Mixed-Integer Linear Programming (MILP)	No
[163]	2017	Power and natural gas networks	Argentinian energy system		Minimization of the operational costs	Mixed-Integer Linear Programming (MILP)	No

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14-node gas system)

costs

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Table A7 (*continued*)

Ref.	Year	Sector(s)	Spatial Resolution	Planning Horizon	Objective	Programming/tool	Co-optimization explicitly mentioned?
				1–3-years planning horizon			
[37]	2017	Power and natural gas networks	Western Danish energy and gas systems	9-year planning horizon	Minimization of the investment and operation costs	Mixed-Integer Nonlinear Programming (MINLP)	No
[162]	2017	Power and natural gas networks (at distribution level)	IEEE 30-bus and 9-node NG system	10-year planning horizon	Minimization of the fixed and operating costs of both electricity and NG systems	Chance Constrained Mixed-Integer Nonlinear Programming (MINLP)	No
[283]	2017	Power and natural gas networks	10-hub electricity system and 10-hub gas network system	1-year planning horizon	Minimization of the investment costs	Integer programming	Yes
[166]	2017	Power and natural gas networks	Great Britain (GB) and Ireland	1-year planning horizon	Minimization of the operational costs	Fico's Xpress Optimisation Suite	Yes
[164]	2018	Power and natural gas networks	IEEE 30-bus electricity system and Belgium gas network	20-year planning horizon	Minimization of the capital and operational cost	Chance constrained Mixed-Integer Linear Programming (MILP)	Yes
[161]	2018	Power and natural gas networks	State of Queensland (Australia)	15-year planning horizon	Minimization of the total system costs	Mixed-Integer Linear Programming (MILP)	No
[284]	2018	Power and natural gas networks	IEEE 30-bus system and Belgian gas network	20-year planning horizon	Minimization of the investment and operational costs	Chance constrained Mixed-Integer Nonlinear Programming (MINLP) – GAMS	No
[38]	2018	Power and natural gas networks	Three case studies (modified 6-bus, IEEE 24-bus and IEEE 118-bus system) with a 11-node gas network	3-year planning horizon	Minimization of the investment and operational costs	Mixed-Integer Linear Programming (MILP)	No
[285]	2018	Power and natural gas networks	Two case studies (modified IEEE 24-bus RTS with a 12-node gas system and a modified IEEE 118-bus power system with the Belgian 20-node NG system)	10-year planning horizon	Minimization of the investment and operational costs	Mixed-Integer Linear Programming (MILP)	Yes
[286]	2018	Power and natural gas networks	Modified IEEE 118-bus power system and a 14-node gas network	n/a	Minimization of the investment and operational costs	Mixed-Integer Linear Programming (MILP)	No
[165]	2018	Power and natural gas networks	Two case studies (Garver's six-bus electricity system with a 5-node NG network and IEEE 24-bus RTS system with the Belgium NG network)	n/a	Minimization of the investment costs	Mixed-Integer Linear Programming (MILP)	Yes
[33]	2019	Power and natural gas networks	Two case studies (modified Garver six-bus power system with a 7-node gas system and a modified IEEE 118-bus system with a 14-node gas system	20-year planning horizon	Minimization of the total co-planning cost	Mixed-Integer Linear Programming (MILP)	Yes
[39]	2019	Power and natural gas networks (at distribution level)	18-node multicarrier system	4-year planning horizon	Minimization of the investment and operational costs	Mixed-Integer Linear Programming (MILP)	No
[287]	2019	Power and natural gas networks	Khorasan province (Iran)	15-year planning horizon	Minimization of the investment and operational costs	Mixed-Integer Nonlinear Programming (MINLP)	No
[157]	2019	Power and natural gas networks	26 node integrated gas-electric system (Eastern region of the U.S.)	20-year planning horizon	Minimization of the investment costs, operational costs, penalties and salvage values	Mixed-Integer Nonlinear Programming (MINLP) and Mixed-Integer Linear Programming (MILP)	Yes
[288]	2019	Power and natural gas networks	IEEE 24-bus system and Belgium NG test system	1-year planning horizon	Minimization of the investment, operational and unsupplied costs	Mixed-Integer Linear Programming (MILP)	No
[167]	2020	Power and natural gas networks	Two case studies (modified IEEE 39-bus system with the Belgium 20-node gas system and a modified 62-bus system with a 25-node natural gas system – China real case)	5-year planning horizon	Minimization of the investment costs	Mixed-Integer Linear Programming (MILP)	Yes
[159]	2020	Power and natural gas networks under extreme events	Two case studies (Garver 6-bus system with a 8-node natural gas network and IEEE 24-bus system and 12-node natural gas network)	5-year planning horizon	Maximization of the value of unserved demand in both the power grid and NG networks	Mixed-Integer Nonlinear Programming (MINLP)	No

Table A8
A literature review on long-term co-optimization in Active Distribution Networks (ADNs) and Micro Grids (MGs).

Ref.	Year	Sector(s)	Spatial Resolution	Planning Horizon	Objective	Programming/tool	Co-optimization explicitly mentioned?
[172]	2020	Power system (ADNs)	Modified 37-bus system	10-year planning horizon	Minimization of the total investment and operation costs	Mixed-Integer Nonlinear Programming (MINLP)	Yes
[175]	2019	Power system (ADNs)	Two case studies (coupled 54-node distribution system and 25-node traffic system)	5-year planning horizon	Minimization of the investment and reliability cost and maximization of the EVs charging service capability	Multi-Objective Natural Aggregation Algorithm (MONAA)	Yes
[289]	2018	Power system (ADNs)	Modified PG&E 69-bus distribution system	10-year planning horizon	Minimization of the total present cost	Mixed-Integer Nonlinear Programming (MINLP)	No
[290]	2018	Power system (ADNs)	18-node distribution network	15-year planning horizon (3 stages of 5 years each)	Minimization of the total investment and operation cost	YALMIP – Matlab	Yes
[170]	2013	Power system (MGs)	MG model	20-year planning horizon	Minimization of the total planning cost	Mixed-Integer Programming (MIP)	Yes
[171]	2018	Power system (MGs)	Multiple-MG operation	20-year planning horizon	Minimization of the total costs	Mixed-Integer Nonlinear Programming (MINLP)	No
[169]	2017	Power system (MGs)	Community MG (State of Ohio)	20-year planning horizon	Minimization of the total annualized cost	GAMS and MATLAB	Yes

Table A9
A literature review on long-term co-optimization between transmission and storage expansion.

Ref.	Year	Sector(s)	Spatial Resolution	Planning horizon	Objective	Programming/tool	Co-optimization explicitly mentioned?
[177]	2017	Storage and transmission expansion planning	Modified 6-bus Garver and IEEE 24-bus systems	n/a	Maximization of the social welfare	Mixed-Integer Linear Programming (MILP)	No
[32]	2017	Storage and transmission expansion planning	Modified IEEE RTS 24-bus system	25-year planning horizon	Minimization of the total operating cost	Stochastic optimization	No
[178]	2017	Storage and transmission expansion planning	WECC 240-bus and 448-line model	Static (single year)	Minimization of the expected operating cost and the investment cost of energy storage.	Mixed-Integer Linear Programming (MILP)	Yes
[179]	2018	Storage and transmission switching operations	Modified IEEE 24-bus power system	Static (single year)	Minimization of the total investment costs	Mixed-Integer Linear Programming (MILP)	Yes
[176]	2018	Storage and transmission expansion planning	Western Electricity Coordinating Council system – WECC (240-bus system)	10-year planning horizon	Tri-level optimization	Mixed-Integer Linear Programming (MILP)	Yes

Table A10
A literature review on long-term co-optimization between energy and transportation systems.

Ref.	Year	Sector(s)	Spatial Resolution	Planning horizon	Objective	Programming/ tool	Co-optimization explicitly mentioned?
[180]	2013	Energy and transportation systems	United States	40-year planning horizon	Minimization of the total system costs	Linear programming	Yes
[181]	2014	Energy and transportation systems	United States	40-year planning horizon	Minimization of the total system costs	Linear programming	Yes
[182]	2015	Energy and transportation systems	United States	40-year planning horizon	Minimization of the total system costs	Linear programming	Yes
[183]	2016	Energy and transportation systems	United States	40-year planning horizon	Minimization of the total system costs	Linear programming	Yes

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