

Heat and electric vehicle flexibility in the European power system: A case study of Norwegian energy communities

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ABSTRACT

This paper investigates sector coupling between the central power system and local energy communities, including heat supply for buildings and charging of electric vehicles. We propose a stochastic linear programming framework to study long-term investments under uncertain short-term operations of nationally aggregated assets. We apply the model to a case study assuming European power sector decarbonization towards 2060 according to a 1.5 degree scenario, and we investigate the impact of coupling building heat systems and electric vehicle charging in Norway with the European power market. The case study focuses on the role of Norway in a European perspective because: (1) Norwegian electricity production is mainly based on flexible and renewable hydropower, (2) Norwegian building heating systems are currently mainly electric, and (3) Norway is already introducing electric vehicles at large. We focus on the European power market to test our hypothesis that it is more cost-efficient to decarbonize when the central power system is coordinated with building heat systems and electric vehicle charging. For Europe as a whole, results show that the average European electricity cost reduces by 3% and transmission expansion decreases by 0.4% when Norwegian heat systems are developed in coordination with the European power system. The average Norwegian electricity cost decreases by 19%. The strategy includes supplying up to 20% of Norwegian buildings with district heating fueled by waste and biomass, and the remaining electric heating supply is dominated by heat pumps.

1. Introduction

European energy policy pursue the growth of variable renewable energy sources (VRES), however, targets for the needed degree of restructuring of the power system are not clearly stated [1]. Integration of VRES will require grid infrastructure, energy storage, flexibility, sector coupling, and short-term fuel switching [2,3], with corresponding changes in market structure and business models [4]. The interest in Zero Energy Buildings [5] is strengthened as buildings in Zero Emission Neighbourhoods [6] are developing towards networks of energy responsive building envelopes [7]. The European Commission highlights the need to facilitate active demand-side participation in future European power markets [8]. This paper studies how the short-term interaction between buildings, electric vehicles (EV), and the central power system affects the long-term energy decarbonization pathway.

Research has demonstrated that the residential sector has an important impact on the aggregated peak load in the European power system [9], and buildings [10] and EVs [11] can facilitate more efficient operation of the power system. However, it is still unclear how the link between the building-, transport-, and power sector can impact European decarbonization.

Several power system models study decarbonization [12] and sector coupling [13]; however, to the authors' knowledge, existing models do not reconcile the following four aspects: (1) multiple long-term investment periods, (2) chronological operational periods, (3) uncertain short-term operations, and (4) short-term sector coupling between the power system, building heat systems, and charging of electric vehicles (EVs). In this context, we propose an extension of The European Model for Power System Investment with (high shares of) Renewable Energy (EMPIRE) [14–16].

Abbreviations: NTC, Net transfer capacity; EU, European Union; EMPIRE, The European Model for Power System Investment with (high shares of) Renewable Energy; CHP, Combined heat and power; VRES, Renewable energy sources; PV, Photovoltaic; EV, Electric vehicle; V2G, Vehicle-to-grid; WtE, Waste-to-Energy; O&M, Operation and maintenance; HWST, Hot water storage tank; COP, Coefficient of performance

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We apply the extended EMPIRE model on a European case study focusing on how heat systems in buildings and charging of EVs are developed and operated when integrated with the European power system. In [17], an assessment of space heating flexibility has been performed, and they call for further work on how identified flexibility can be utilized in a larger context. In [18], they find that EV charging load could exceed available electricity capacity in some European countries and that flexible EV charging could limit some capacity inadequacy. In this paper, we focus on how sector coupling affects the development of conventional flexibility assets, e.g. hydropower, and flexibility from heat systems in buildings and smart charging of EVs. Norway is in focus because its electricity supply is dominated by flexible hydropower, building heat systems are mainly electric, and EVs are phased in by favorable policies. Our hypothesis is that increasing the flexibility of building heat systems and EV charging in Norway will benefit the European power system as a whole because flexible Norwegian hydropower can be utilized as a ‘green battery’ in Europe [19,20]. Essentially, we test whether adding more flexibility to an already flexible region of the power system can benefit the whole system. The case study analyzes how sector coupling affects the development of: generation assets for building heat and electricity, power transmission assets, and storage and flexibility assets, including hydropower, building heat, and EVs.

The structure of the paper is as follows: Section 2 presents related research to identify the novelty of our modelling framework and our case study. Section 3 presents the modelling framework including the new sector coupling features of EMPIRE, and Section 4 presents the European case study. Finally, Section 5 presents and discusses the case study results, before the paper is concluded in Section 6.

2. Background

This section discusses several techno-economic energy system models that have been used for analyses of European decarbonization towards 2050.

A comprehensive multi-scale analysis is presented in [21] investigating transition pathways towards the EU low carbon economy [22] without considering endogenous uncertainty within the modeling frameworks. In [23], short-term uncertainty in long-term energy system models is shown to be important when considering VRES like wind. The E2M2 model considers short-term uncertainty of VRES in [24], but storage and demand response technologies are not considered. Flexibility in a VRES dominated power system, including transmission, has been studied in The North Sea region using the PowerGIM model in [25] without considering sector coupling. The Balmorel model has been used to analyze sector coupling between the heat and electricity sectors [26–28], but does not consider short-term uncertainty of VRES.

The German heat and electricity sector has been studied with the REMod-D model [29] and results show that 100% renewable supply is feasible [30]. The Nordic and Baltic region is analyzed with Balmorel in [27] where they find that electricity-to-heat converters and hot water storage tanks (HWST) are important assets. Increased flexibility in electricity systems dominated by combined heat- and power (CHP) plants through HWST and electric boilers are shown to decrease wind curtailment in [31]. Integrated operation of electricity and district heating systems has been analyzed in [32] demonstrating reduced operational costs, and the theoretical maximum of flexibility from CHP systems coupled with HWST have been analyzed in [33]. Price effects on electricity based heating in Norway are analyzed with Balmorel in [28] where they find that fuel switching in heat systems have growing importance with more VRES in the power system. Both heat and electricity is considered in a stochastic version of TIMES in [34] studying the impact of net Zero Energy Buildings in the Scandinavian energy system. In [34], they find that such buildings will (1) partly replace

investments in non-flexible hydropower, wind power and (CHP) and (2) trigger investments in more electricity based heating systems. Europe as a whole has been studied in [35] focusing on the utilization of excess production by VRES for building heating, and they find that heat pumps are a preferred technology to perform the sector coupling. In [36], the PyPSA [37] framework has been used to study sector coupling between the European power system, the heat sector, and the transport sector in 2050, and they find that transmission exchange combined with energy flexibility through sector coupling can reduce total system costs of decarbonization by 37%.

The EMPIRE model has been used to analyze decarbonization of the European power system considering uncertainty [14]. An updated version of EMPIRE is presented in [15] explaining the multi-horizon stochastic programming structure [38], and a case study of the European power system decarbonization shows large wind power expansion and major net transfer capacity (NTC) expansion between European countries [15]. Demand response features have also been developed in EMPIRE [16] and tested in a European case study. EMPIRE has been linked with the model ZENIT in [39] to analyze how energy resources in neighbourhoods integrate into the Nordic power system, but only considers contributions of electricity production from neighbourhoods.

In summary, we identify two research gaps: (1) The lack of a modeling framework consolidating long-term energy system planning, short-term uncertainty, and sector coupling, and (2) the lack of a previous study focusing on the Norwegian sector coupling with a European perspective. To cover these gaps, the continuation of this paper proposes a modeling framework (Section 3) and a case study (Section 4).

3. Method

This section presents the stochastic programming model EMPIRE [14–16] which has been re-implemented in the open-source Python-based optimization suite Pyomo [40].

3.1. Model structure

EMPIRE [14–16] is a techno-economic capacity expansion model [41] applied to the European energy system represented by a network. An open version of EMPIRE can be downloaded from [42]. The nodes in the network represent auction zones for clearing energy supply and demand, and the arcs represent exchange of electricity between these zones. The model supports investment decisions in generation, storage, and transmission assets on a country/zonal level made subject to the need to meet energy demand on an hourly basis without exceeding a European-wide emission cap. Energy demand, as well as asset options, their related costs and operational characteristics, are input to the model. The output supports decisions regarding technology choices, investment volume and timing, as well as hourly operations assuming perfect competition. Investments and operations related to generation and storage capacity happen in the nodes, cross-border exports and imports are described by arcs, whereas investments in transmission are described by a pair of unidirectional arcs between the same two nodes.

EMPIRE forms a linear two-stage stochastic program [43] where the first-stage decisions represent investments in period i , and the second-stage decisions represent operations in period i and scenario ω . The stochastic scenarios consider uncertainty in the availability of wind-, solar-, hydropower generation; electric specific and building heat load; coefficient of performance (COP) for heat pumps; and required energy for flexible demand, e.g. EV charging. EMPIRE uses a multi-horizon structure [38] illustrated in Fig. 1. Each scenario $\omega_{x,y,z}$ represents time series, and scenario z represents one realization of season y in investment period x .

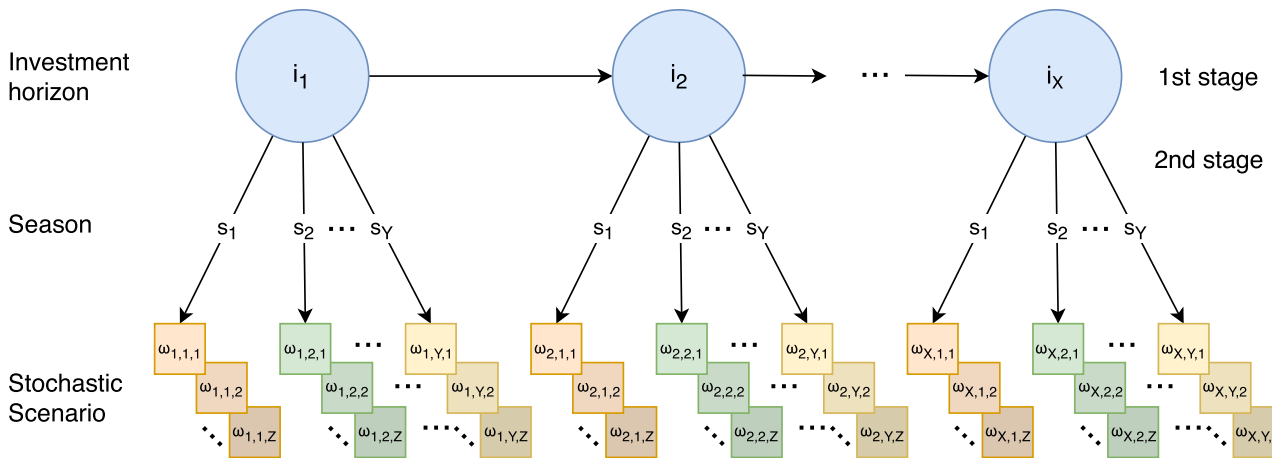


Fig. 1. Illustration of the stochastic structure of the EMPIRE model. The blue circles represent investment periods with first-stage decisions, and each period contains seasons and stochastic scenarios with second-stage decisions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2. Sector coupling features

3.2.1. Building heat

One of the contributions of this paper is the development of EMPIRE to include sector coupling of building heat systems with the central power system. This feature is developed by categorizing energy demand into electric specific demand and building heat demand as described in [44]. Electric specific demand includes all electricity demand that *must* be met with electricity, while building heat demand includes space and hot water demand in buildings that *can* be met with either electricity or other heat producing technologies, e.g. district heating. The model supports investments in technologies that can generate and store heat and electricity, including CHP plants. In addition, the model supports investment in technologies converting electricity to heat, e.g. heat pumps. Through the electricity-to-heat converters, it is feasible to satisfying building heat demand with 100% electricity.

Fig. 2 represents the link between operations in a specific node, operational period, investment period, and stochastic scenario. Supply by generators is either electricity, heat, or both (CHP). Converters transform electricity to heat but not heat to electricity. Generators and converters must satisfy electric specific and building heat demand. More electricity and heat in one operational time step can be supplied or converted to be stored for later within the same season and stochastic scenario. If there is less supply than demand for electricity or heat, storage must be discharged or load must be shed. Heat, naturally,

cannot be exchanged between countries.

Fig. 2 also illustrates how the model considers flexibility from supply-, converter-, and storage assets. For every hour, the model has flexibility to cover electricity demand by producing electricity in that hour or discharging stored electricity. Similarly for heat, there is flexibility to produce or discharge stored heat to cover heat demand, and additionally an option of converting electricity to heat with either produced or stored electricity. Note that demand is not considered flexible. However, the model can consider demand flexibility if parts of the demand is considered as a storage. Charging the storage is equivalent to the net addition of demand in an hour, while discharging the storage is equivalent to net removal of demand in an hour.

3.2.2. Electric vehicle charging

To consider flexible EV charging, the demand response features of EMPIRE presented in [16] are used. More specifically, EV demand is considered to be a *shiftable volume load* [16], i.e. energy demand that must be met by a certain time period with any charging pattern given it meets the energy demand and satisfies some charging constraints. The input of EV demand affects the total EV charging flexibility, and it is the minimum cumulative charging to be made within a node and period, e.g. every 24 h. We consider uncertainty of EV flexibility by allowing EV demand to vary across different stochastic scenarios. The charging constraints also affect the EV charging flexibility for every node and investment period, and they include a maximum charging limit

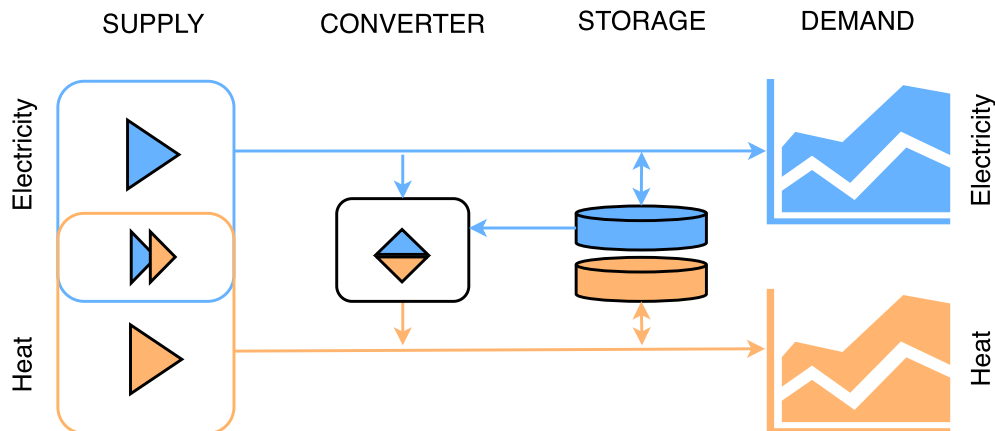


Fig. 2. Illustration of the sector coupling between the electricity and the building heat sector in the EMPIRE model. The sector coupling is on an hourly time resolution in the model.

dependent on the endogenous EV charging capacity expansion. We also consider vehicle-to-grid (V2G) through the possibility of discharging EVs.

3.3. Mathematical formulation

The following section presents in detail the mathematical formulation of EMPIRE used in this paper including the developments presented in Section 3.2. It is best read assisted by the full nomenclature of EMPIRE found in Appendix A.

3.3.1. Objective function

The objective function in EMPIRE quantifies costs of investing and operating the respective energy system, and it is formulated in the following way:

$$\begin{aligned} \min z = & \sum_{i \in I} (1+r)^{-5(i-1)} \times \\ & \left[\sum_{n \in N} \sum_{a \in \mathcal{G}_n \cup \mathcal{B}_n \cup \mathcal{R}_n} c_{a,i}^{\text{node}} x_{a,n,i}^{\text{node}} + \sum_{n \in N} \sum_{b \in \mathcal{B}_n} c_{b,i}^{\text{storCH}} x_{b,n,i}^{\text{storCH}} + \right. \\ & \sum_{(n_1, n_2) \in \mathcal{L}} c_{n_1, n_2, i}^{\text{tran}} x_{n_1, n_2, i}^{\text{tran}} + \\ & \vartheta \sum_{\omega \in \Omega} \pi_{\omega} \sum_{s \in S} \alpha_s \sum_{h \in \mathcal{H}_s} \sum_{n \in N} \sum_{g \in \mathcal{G}_n} q_{g,i}^{\text{gen}} y_{g,n,h,i,\omega}^{\text{gen}} + \\ & \left. \vartheta \sum_{\omega \in \Omega} \pi_{\omega} \sum_{s \in S} \alpha_s \sum_{h \in \mathcal{H}_s} \sum_{n \in N} (q_{n,i}^{\text{ll,EL}} y_{n,h,i,\omega}^{\text{ll,EL}} + q_{n,i}^{\text{ll,HT}} y_{n,h,i,\omega}^{\text{ll,HT}}) \right]. \quad (1) \end{aligned}$$

The objective function (1) discounts all costs at an annual rate of r , and the investment periods are given as five-year blocks. The first three terms of (1) relates to investment costs in additional capacity of generation, storage, and transmission. The last three terms relate to operational- and load shedding costs. The terms for operational costs are scaled with the scenario probability π_{ω} , the seasonal scaling factor α_s annualizing the seasonal costs, and the five-year scale factor $\vartheta = \sum_{j=0}^4 (1+r)^{-j}$ scaling and discounting the annual operational costs to the five-year investment periods.

3.3.2. Investment constraints

Installed capacity of assets in each period is defined in the following way:

$$\begin{aligned} v_{a,n,i}^{\text{node}} = & \bar{x}_{a,n,i}^{\text{node}} + \sum_{j=i'}^i x_{a,n,j}^{\text{node}}, \\ a \in & \mathcal{G}_n \cup \mathcal{B}_n \cup \mathcal{R}_n, n \in N, i \in I, i' = \max\{1, i - i_a^{\text{life}}\}. \quad (2) \end{aligned}$$

Constraints (2) make sure installed capacity is defined as initial capacity plus capacity expansion up until the period of consideration for every generator, storage, and electricity-to-heat converter. Note that constraints (2) consider the asset lifetime. Equivalent constraints also apply for transmission lines and charging/discharging capacity of storage.

Capacity expansion of storage is separate for charging/discharging capacity and energy storage capacity. However, some storage technology types $b \in \mathcal{B}^{\dagger} \subseteq \mathcal{B}$ cannot expand charging/discharging capacity without also expanding energy storage capacity. A fixed capacity expansion ratio, β_b^{stor} , is defined for $b \in \mathcal{B}^{\dagger}$, and constraints (3) apply:

$$v_{b,n,i}^{\text{storCH}} = \beta_b^{\text{stor}} v_{b,n,i}^{\text{node}}, \quad b \in \mathcal{B}^{\dagger} \cap \mathcal{B}_n, n \in N, i \in I. \quad (3)$$

3.3.3. Operational constraints

There are two main groups of equations in EMPIRE that ensure the operational balance between supply and demand of electric specific and building heat load:

$$\begin{aligned} & \sum_{g \in \mathcal{G}_{\text{EL}} \cap \mathcal{G}_n} \beta_g^{\text{CHP}} y_{g,n,h,i,\omega}^{\text{gen}} + \sum_{b \in \mathcal{B}_{\text{EL}} \cap \mathcal{B}_n} \eta_b^{\text{dischrg}} y_{b,n,h,i,\omega}^{\text{dischrg}} + \\ & \sum_{(n_1, n_2) \in \mathcal{A}_n^{\text{in}}} \eta_{n_1, n_2}^{\text{tran}} y_{n_1, n_2, h, i, \omega}^{\text{tran}} + y_{n, h, i, \omega}^{\text{ll, EL}} = \xi_{n, h, i, \omega}^{\text{load, EL}} + \\ & \sum_{b \in \mathcal{B}_{\text{EL}} \cap \mathcal{B}_n} y_{b, n, h, i, \omega}^{\text{chrg}} + \sum_{(n_1, n_2) \in \mathcal{A}_n^{\text{out}}} y_{n_1, n_2, h, i, \omega}^{\text{tran}} + \sum_{r \in \mathcal{R}_n} y_{r, n, h, i, \omega}^{\text{E2H}}, \\ n \in N, h \in \mathcal{H}, i \in I, \omega \in \Omega, \quad (4) \end{aligned}$$

$$\begin{aligned} & \sum_{g \in \mathcal{G}_{\text{HT}} \cap \mathcal{G}_n} y_{g, n, h, i, \omega}^{\text{gen}} + \sum_{b \in \mathcal{B}_{\text{HT}} \cap \mathcal{B}_n} \eta_b^{\text{dischrg}} y_{b, n, h, i, \omega}^{\text{dischrg}} + \\ & \sum_{r \in \mathcal{R}_n} \eta_{n, r, h, i, \omega}^{\text{E2H}} y_{r, n, h, i, \omega}^{\text{E2H}} + y_{n, h, i, \omega}^{\text{ll, HT}} = \\ & \xi_{n, h, i, \omega}^{\text{load, HT}} + \sum_{b \in \mathcal{B}_{\text{HT}} \cap \mathcal{B}_n} y_{b, n, h, i, \omega}^{\text{chrg}}, \\ n \in N, h \in \mathcal{H}, i \in I, \omega \in \Omega. \quad (5) \end{aligned}$$

Constraints (4) ensure the balance of electric specific load, which means that total supply from electric generators and storage units, as well as imports and electric load shedding, must be balanced with electric load, exports, and charging. Note that $\beta_g^{\text{CHP}} = 1$ for all $g \notin \mathcal{G}_{\text{EL}} \cap \mathcal{G}_{\text{HT}}$, that is all non-CHP electric generators. For CHP generators ($g \in \mathcal{G}_{\text{EL}} \cap \mathcal{G}_{\text{HT}}$), β_g^{CHP} represents how much electricity is being produced per unit of heat output.

Similarly, constraints (5) make sure the building heat load is balanced such that total supply from building heat generators and storage units, as well as conversions of electricity to heat and heat load shedding, must be balanced with heat load and charging. Note that conversion of electricity to heat links constraints (4) and (5) together, and that hourly scenario dependent converter efficiency is ensured in constraints (5).

Annual CO₂eq. emissions from energy production for every investment period are restricted with an emission cap:

$$\begin{aligned} \sum_{s \in S} \alpha_s \sum_{h \in \mathcal{H}_s} \sum_{n \in N} \sum_{g \in \mathcal{G}_n} q_{g,i}^{\text{CO}_2} y_{n, g, h, i, \omega}^{\text{gen}} \leq Q_i^{\text{CO}_2}, \\ i \in I, \omega \in \Omega. \quad (6) \end{aligned}$$

Constraints (6) ensure that no operational scenario can produce more annual CO₂eq. emissions than the cap allows. These constraints ensure that the optimal solution of EMPIRE represents an energy system with the needed emission reductions, while the objective (1) is focusing on minimizing total system costs. The alternative to including the carbon cap constraints (6) is to include carbon pricing as part of the operational costs of carbon emitting generators. However, future carbon prices are harder to forecast than future carbon caps, so we include constraints (6). Note that the dual variables of constraints (6) represent the shadow prices of meeting the carbon cap which makes carbon prices an output of EMPIRE.

Generators are subject to the following operational constraints:

$$\begin{aligned} y_{g,n,h,i,\omega}^{\text{gen}} \leq \xi_{g,n,h,i,\omega}^{\text{gen}} v_{g,n,i}^{\text{node}}, \\ g \in \mathcal{G}_n, n \in N, h \in \mathcal{H}, i \in I, \omega \in \Omega, \quad (7) \end{aligned}$$

$$\begin{aligned} y_{g,n,h,i,\omega}^{\text{gen}} - y_{g,n,h-1,i,\omega}^{\text{gen}} \leq \gamma_g^{\text{gen}} v_{g,n,i}^{\text{node}}, \\ g \in \mathcal{G}_{\text{Ramp}} \cap \mathcal{G}_n, n \in N, s \in S, \\ h \in \{h_s^2, \dots, |\mathcal{H}_s|\}, i \in I, \omega \in \Omega. \quad (8) \end{aligned}$$

Constraints (7) ensure that generator type g cannot produce more than what is installed in node n and period i and what is available in hour h and scenario ω . Thus, constraints (7) allow for the consideration of uncertain availability of e.g. VRES. Constraints (8) ensure that some generators are subject to up-ramping restrictions, i.e. increasing generator output between two consecutive hours is limited by a share of installed capacity.

Hydroelectric generators are subject to additional constraints:

$$\sum_{h \in \mathcal{H}_s} y_{n,i,s,\omega}^{\text{RegHyd}'} \leq \xi_{n,i,s,\omega}^{\text{RegHydLim}}, \quad (9)$$

$$n \in \mathcal{N}, s \in \mathcal{S}, i \in \mathcal{I}, \omega \in \Omega,$$

$$\sum_{\omega \in \Omega} \pi_{\omega} \sum_{s \in \mathcal{S}} \alpha_s \sum_{h \in \mathcal{H}_s} \sum_{g \in \mathcal{G}^{\text{Hyd}} \cap \mathcal{G}_n} y_{n,g,h,i,\omega}^{\text{gen}} \leq \xi_n^{\text{HydLim}}, \quad (10)$$

$$n \in \mathcal{N}, i \in \mathcal{I}.$$

Generation by regulated hydro plants is restricted by season and node through constraints (9), while expected annual production for all hydro plants in a node are constrained by (10)

Storage assets are subject to the following operational constraints:

$$\kappa_b v_{n,b,i,\omega}^{\text{node}} + \eta_b^{\text{chrg}} y_{n,b,h_s^1,i,\omega}^{\text{chrg}} - y_{n,b,h_s^1,i,\omega}^{\text{discrg}} = w_{n,b,h_s^1,i,\omega}^{\text{stor}}, \quad (11)$$

$$b \in \mathcal{B}_n, n \in \mathcal{N}, s \in \mathcal{S}, i \in \mathcal{I}, \omega \in \Omega,$$

$$w_{b,n,h-1,i,\omega}^{\text{stor}} + \eta_b^{\text{chrg}} y_{b,n,h,i,\omega}^{\text{chrg}} - y_{b,n,h,i,\omega}^{\text{discrg}} = \eta_b^{\text{bleed}} w_{b,n,h,i,\omega}^{\text{stor}}, \quad (12)$$

$$b \in \mathcal{B}_n, n \in \mathcal{N}, s \in \mathcal{S}, h \in \{h_s^2, \dots, |\mathcal{H}_s|\},$$

$$i \in \mathcal{I}, \omega \in \Omega.$$

$$w_{n,b,h_s^1,i,\omega}^{\text{stor}} = w_{n,b,|\mathcal{H}_s|,i,\omega}^{\text{stor}}, \quad (13)$$

$$b \in \mathcal{B}_n \setminus \mathcal{B}_{\text{FX}}, n \in \mathcal{N}, s \in \mathcal{S}, i \in \mathcal{I}, \omega \in \Omega,$$

$$\xi_{n,h,i,\omega}^{\text{FX}} \leq w_{n,b,h,i,\omega}^{\text{stor}}, \quad (14)$$

$$b \in \mathcal{B}_{\text{FX}}, n \in \mathcal{N}, h \in \mathcal{H}, i \in \mathcal{I}, \omega \in \Omega.$$

Storage assets start with an initial energy level available as a percentage of installed capacity ensured by constraints (11), and their state of charge considering losses is ensured by constraints (12). Normal storage assets run a full cycle over each representative time period in each season through (13), while flexible demand, $b \in \mathcal{B}_{\text{FX}}$, is represented as storage that needs to be filled by specified hours within representative periods through constraints (14).

Flexibility in EMPIRE is related to an asset's ability to adapt its operation to different operational scenarios, and it can be provided by all assets in EMPIRE, including generators, storage, transmission, and electricity-to-heat converters. The generators with more operational constraints, like generators subject to ramping constraints (8), have less flexibility than generators without ramping constraints, e.g. regulated hydropower.

3.3.4. Other constraints

In addition to the constraints presented in the previous section, all variables in EMPIRE are subject to non-negativity constraints. Capacity expansion is subject to upper bounds, and all asset operations are bounded by installed capacity.

4. Case study

This section describes our European case study and the input to the EMPIRE model. The main purpose of the case study is to study the impact of the sector coupling features presented in Section 3.2 with a European perspective.

We consider eight five-year investment periods from 2020 to 2060, and we assume an annual discount rate of 5% following [14]. The instances contain 35 nodes¹ and 85 bidirectional arcs representing existing and potential European power exchanges. Norway is divided into five nodes representing the Norwegian Nord Pool price zones. No transmission expansion between the Norwegian zones is allowed. The CO2eq. cap is assumed to follow [45] from 1, 110 to 22 Mton CO2eq. per year from 2020 to 2060. Emission factors for stationary combustion are estimated according to [46], and we assume only operational emissions and no emissions related to VRES including biomass. Cost of

Table 1

Heat technology capital costs gathered from [48]. All generators are assumed to supply a district heating grid. CHP = Combined Heat and Power, HOP = Heat Only Plant (no electricity generation).

| Technology | Capital cost [€/kW-heat] | | |
|--------------------------------|--------------------------|---------|---------|
| | '20-'30 | '30-'45 | '45-'60 |
| Converter | | | |
| Convector | 966.7 | 933.3 | 833.3 |
| Heat Pump (air-to-air) | 440.0 | 514.3 | 485.7 |
| Generator | | | |
| Waste-to-Energy (CHP) | 1870.0 | 1780.0 | 1610.0 |
| Waste-to-Energy (HOP) | 1840.0 | 1750.0 | 1640.0 |
| Bio Wood Chip (CHP) | 1000.0 | 950.0 | 880.0 |
| Bio Wood Chip (HOP) | 790.0 | 750.0 | 680.0 |
| Storage | | | |
| Hot Water Storage Tank (small) | 410.0 | 410.0 | 410.0 |
| Hot Water Storage Tank (large) | 150.0 | 150.0 | 150.0 |

load shedding is assumed to be €22, 000/MWh following [47].

We include 16 electricity generator types and two electricity storage types (see Appendix B), and we do not consider carbon capture and storage technologies. Additionally, we consider two electricity-to-heat converter types, two non-electric building heat generator types, two CHP generator types, and two heat storage types (see Table 1). Technology costs for electricity generators come from [49], and fuel costs come from [50]. For building heat technologies, costs come from [48]. Costs for transmission expansion is according to [15].

Operational scenarios have an hourly resolution and consist of six seasons per investment period: four regular seasons and two peak seasons. The regular seasons have 168-h duration and the peak seasons have 24-h duration. We consider three stochastic scenarios for all seasons. The uncertain data input are: VRES availability, load, COP for heat pumps, and EV demand.

Based on historical data, uncertainty related to VRES availability and load are produced by the scenario sampling routine described in [15]. The sampling routine is initiated by defining four partitions of a year containing hourly data that represents four regular seasons. The data set we sample from consist of several years of data for VRES availability from renewables.ninja [51,52] and load from ENTSO-E Transparency Platform. The sampling routine consist of the following steps: (1) selecting a random year, (2) selecting randomly the same 168 consecutive hours for each stochastic process within a season, and (3) repeating the former step for all seasons. The sampling routine is performed for all scenarios, and it is repeated for any sampled scenario that deviates too much from the mean, variance, skewness, and kurtosis of the respective underlying full data set. To represent extreme situations, we also construct two peak seasons containing 24 consecutive hours of extreme load situations. The first peak day contains the highest load summed over all countries, and the second peak day contains the highest hourly load of a single country. For heat pumps, we sample temperatures in Norway for the same hours for the year 2016, and we perform a linear regression based on data for BOSCH BMS500-AAM018-1CSXXA [53] to estimate a temperature dependent time series for the COP assuming an indoor temperature of 22 degrees.

As we consider the stochastic processes of load and VRES availability across Europe to be complex and mutually dependent, we sample from historical observations chronologically to preserve auto-correlation. Additionally, the same historic hours are sampled for the different European countries to preserve spatial cross-correlation. We also sample the same hours of a year for the different stochastic input to further preserve cross-correlation between the stochastic processes.

¹ The model includes nodes for all countries in the EU-27 minus Cyprus and Montenegro plus Bosnia Hercegovina, Great Britain, North Macedonia, Serbia, Switzerland, and five Norwegian nodes representing Nord Pool bidding zones.

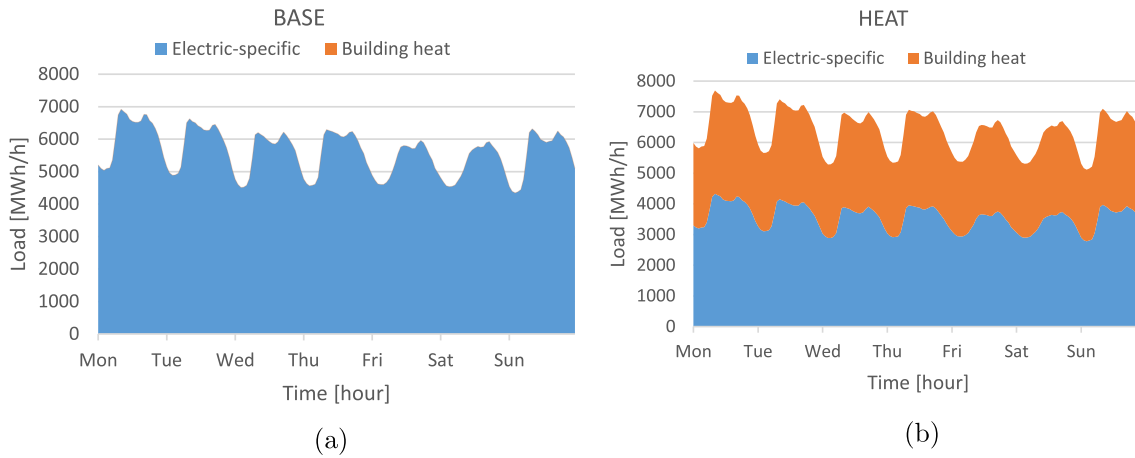


Fig. 3. A winter week for NO1 in BASE (a) and HEAT (b). All load is defined as electric specific load based on historic load profiles in BASE, whereas 40% and 20% of this load is defined as building heat load in HEAT for Norwegian winter and summer seasons, respectively.

Regarding uncertainty related to EV demand, we consider annual EV demand in Norway as projected in [54], from 2 TWh/year in 2020 to 15 TWh/year by 2060. Note that EV demand includes not only cars, but also buses and ferries [55]. The annual EV demand is made into a constant 24-h demand with a $\pm 5\%$ random variability across the three stochastic scenarios.

We define two European instances in EMPIRE for comparison:

- BASE: All load in Europe is electric specific (see Fig. 3a) without defining building heat load. All load can only be met with electricity generation.
- HEAT: Part of Norwegian total load is defined as building heat load (see Fig. 3b). Heat load can be met with electricity-to-heat converters, including heat pumps and convectors, or non-electric heat generation and heat storage (see Table 1).

We only consider building heat load in Norway because we hypothesize that flexible Norwegian hydropower is more valuable for other purposes in the coming decades than meeting building heat load. Norwegian building heat supply is currently largely electric, while Norwegian electricity generation is dominated by flexible hydropower. Statistics from [56,54] show that 60% of electricity demand in buildings is for heating purposes and buildings make up about half of the total Norwegian electricity demand. Thus, the heat load in HEAT is estimated as 40% and 20% of the hourly electricity load from BASE for the Norwegian nodes for winter and summer seasons, respectively (see Fig. 3b). To make a fair comparison, the sum of heat and electricity demand is equal for BASE and HEAT if building heat load is met with existing building heat systems. Note in Fig. 3 that the total hourly load is higher in HEAT compared to BASE as the building heat load is adjusted by the COP of heat pumps. Defining building heat load as a share of historic electricity load can be used for Norway as heat supply to buildings is mainly electric [56], however, other approaches for projecting building heat load should be used for countries where building heat is not mainly covered with electricity, see e.g. [29,44].

To project future load profiles, we shift historic load profiles according to energy demand forecasts. This is done by calculating two averages: (1) the average load in node n in the first investment period ($i = 1$) based on the historic load profile for one stochastic scenario ω ($\xi_{n,1,\omega}^{\text{load,avg}}$) and (2) the average demand in one hour based on the annual demand estimate from the EU reference scenario [50] for investment period i ($\xi_{n,i}^{\text{dem,avg}}$). The load $\xi_{n,h,i,\omega}^{\text{load}}$ in hour h in node n , investment period i , and scenario ω is then calculated $\forall h \in \mathcal{H}$:

$$\xi_{n,h,i,\omega}^{\text{load}} = \xi_{n,h,1,\omega}^{\text{load}} - \xi_{n,1,\omega}^{\text{load,avg}} + \xi_{n,i}^{\text{dem,avg}}.$$

Electricity load data are based on historic load from ENTSO-E and shifted according to the annual demand growth anticipated in the EU decarbonization scenario 2016 presented in [50] towards 2050 and a linear interpolation towards 2060. For Norway, we estimate the annual electricity demand towards 2040 according to [54] and a linear interpolation for following investment periods in BASE. In HEAT, we categorize the annual electricity demand into electric specific demand for all sectors and building heat demand according to [54,56] adjusted by the COP of heat pumps (see Fig. 4). We allocate the annual demand within Norway according to the historical share of the total annual electricity use of the five Nord Pool zones, and this allocation method is used for any data related to Norway unless otherwise stated.

In both BASE and HEAT, investment costs for EV charging infrastructure are estimated according to Table 5.5 in [57]. We estimate initial charging capacity in Norway to be 300 MW assuming 15,000 charging stations with an average capacity of 20 kW based on [58]. We assume existing charging capacity is retired by 2030 and allocate the initial capacity according to the share of publicly available car charging stations in each Norwegian zone in 2018 presented in [59]. We assume no losses related to EV charging. We also allow 20% of EV charging capacity to be used for V2G without costs or losses.

Initial electricity generation capacity per country is estimated according to [60]. We also assume only initial electricity-to-heat converters in buildings in Norway estimated as a share of peak heat load in each node as presented in [61]: 28% for heat pumps adjusted by the COP and 72% for convectors. We assume no fuel costs for Waste-to-Energy (WtE) generators. Because of waste treatment constraints, we also assume output from WtE generators must remain constant in each season with no intra-weekly up-ramping. The maximum installed capacity of WtE in Norway is estimated to be 1,140 MW². Emissions from burning waste are assumed to be 37.0 kgCO₂e/GJ according to [48]. For the bio-based heat generation, fuel costs are chosen according to [50]. For initial capacity of HWSTs in Norway, we assume a Norwegian population of 5.3 million according to [63] and 1 kWh energy and charging capacity of small HWST capacity per person³, and we assume no retirement of initial HWST capacity.

The energy community flexibility in our case study is related to HWST and charging/discharging of EVs, and we do not consider

² According to [62], Norway produces 3.6 million tons of burnable waste annually, and an energy value of 2.78 MWh/ton [48] can at maximum produce 10,000 GWh/year, or 1,140 MWh/h.

³ One tank has 3 kWh energy capacity on average [48], and we assume two persons per tank and that two thirds of the tank is available for flexibility

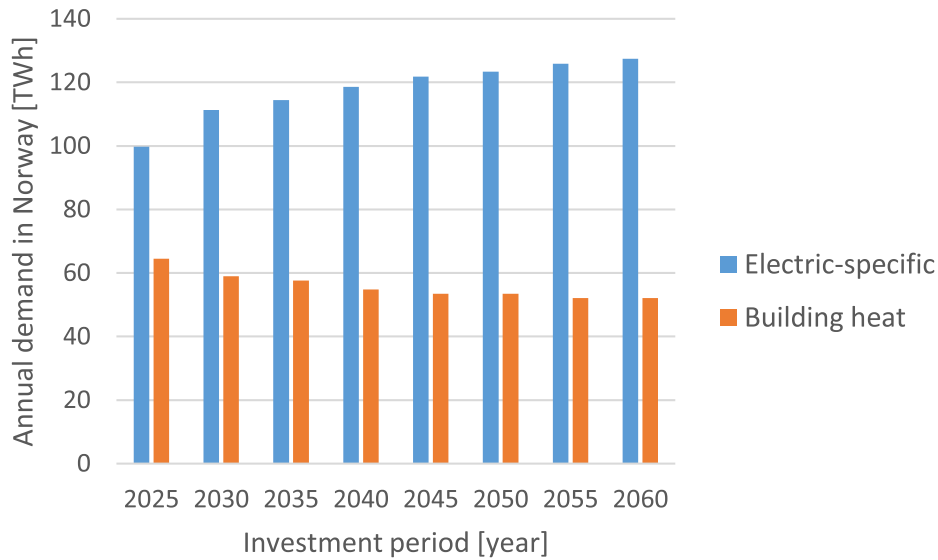


Fig. 4. Assumed development of annual electric specific and heat demand in Norway in HEAT.

flexibility in the thermal mass of buildings or other controllable loads in the communities.

5. Results and discussion

This section presents the results from our case study described in Section 4. BASE is solved in 9,000 seconds, while HEAT is solved in 11,000 seconds using interior point method (barrier algorithm) [64] without crossover with the FICO® Xpress Solver v8.8.1 [65] running on a computer cluster with CPU 2x 4 GHz Intel E5-2643v3 (6 core) and 512 Gb RAM.

5.1. Total system costs and emissions

The total discounted system costs for Europe from 2020 to 2060 for

BASE is €2.47 trillion or an average undiscounted cost of European electricity of €100/MWh. In HEAT, 1% of total European electricity demand is identified as building heat demand in Norway. In BASE, all demand is assumed to be electric specific, so the main difference between BASE and HEAT is that building heat demand can be met by non-electric heat supply or more efficient electricity-to-heat converters in HEAT. This opportunity reduces the total system cost for Europe by €7.14 billion (-0.29%) in HEAT, which means discounted savings of €3.2/MWh of building heat demand. The average undiscounted cost of European electricity reduces to €96/MWh (-4%) in HEAT. The total number of hours with electricity prices > €1,000/MWh reduces by 19% and the number of hours with prices < €1/MWh reduces by 5% in HEAT compared to BASE. The undiscounted average cost of electricity in Norway is €86/MWh in BASE and reduces to €70/MWh (-19%) in HEAT.

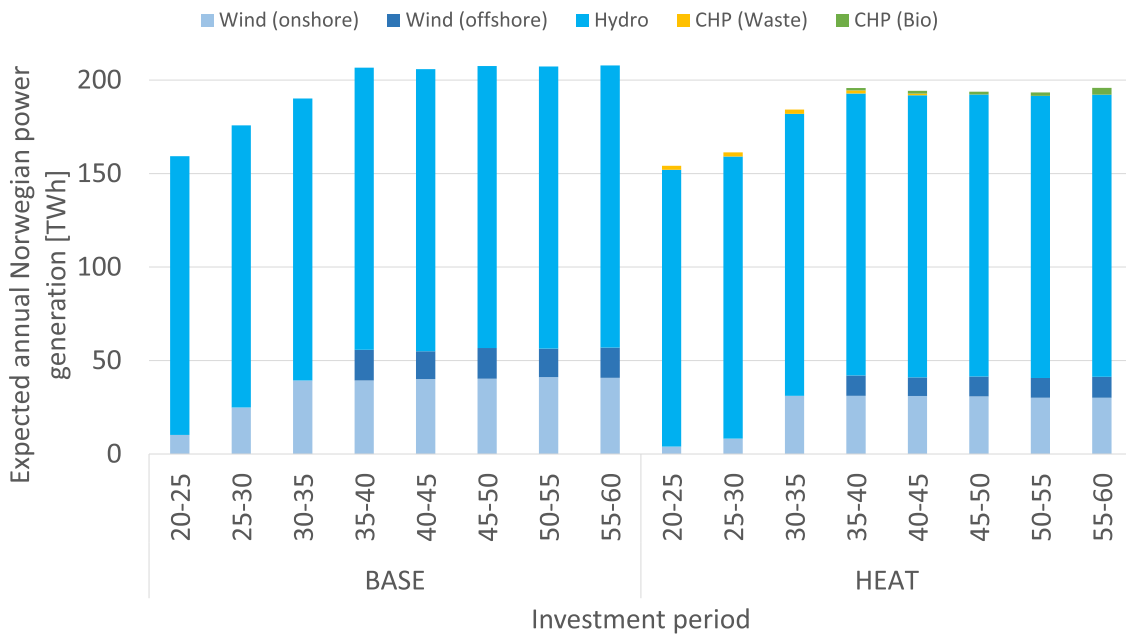


Fig. 5. Expected annual electricity generation from all Norwegian zones (NO1-NO5) from 2020 to 2060.

Table 2
Total expected demand and generation in Norway for BASE and HEAT from year 2020 to 2060.

| Instance | BASE | HEAT |
|---|-------|-------|
| Electric specific demand, Norway [TWh] | 6,200 | 4,700 |
| Building heat demand, Norway [TWh] | – | 2,200 |
| Expected electricity generation, Norway [TWh] | 7,800 | 7,400 |
| – of which hydro [TWh] | 6,000 | 6,000 |
| – of which wind [TWh] | 1,800 | 1,200 |
| – of which CHP [TWh] | – | 100 |
| Expected non-electric heat generation, Norway [TWh] | – | 400 |
| Expected electric heat generation, Norway [TWh] | – | 1,900 |
| – of which convector [TWh] | – | 300 |
| – of which heat pump [TWh] | – | 1,600 |

Total expected European emissions are capped for all generators, including heat generators, according to [45] and binding for all investment periods in BASE and HEAT. This is because of the emission cap constraints (6) in Section 3.3 which ensure that the scenarios with the highest emissions in all investment periods have the same emissions in BASE and HEAT. Note that both instances satisfy the emission targets in [45] for all investment periods. The undiscounted CO₂eq. price ranges between €40/ton and €60/ton until 2040, and increases beyond €100/ton after 2040. The highest indicated CO₂eq. price is €974/ton from 2055 to 2060 in BASE.

5.2. Expected annual heat and electricity generation

Hydropower dominates Norwegian electricity generation for both instances (see Fig. 5), while onshore- and offshore wind grows towards 2060 in both instances (see Fig. 5). Total electricity production in Norway, mainly from wind, is decreased in HEAT compared to BASE (see Table 2), while total expected hydropower output is the same.

Decreased electricity production in HEAT compared to BASE is because of two reasons: (1) building heat supply is met by CHP plants incinerating waste and biomass and (2) energy efficiency is increased through increased use of heat pumps. Up to 20% of building heat supply comes from CHP plants in HEAT, while the remaining building heat

demand is met with electricity mainly used in heat pumps (see Fig. 6). The CHP plants are fueled solely by municipal waste until 2035, while emission constraints ensure an increasing amount of biomass is burned towards 2060. For the European power system as a whole, onshore- and offshore wind is decreased in HEAT compared to BASE compensated by energy from CHP plants and efficiency gains through heat pump use in Norway (see Fig. 7).

5.3. Transmission

Norwegian expected annual electricity imports decrease by 4% and exports increase by 8% in HEAT compared to BASE (see Fig. 8). The increased Norwegian electricity exports in HEAT compared to BASE does not lead to increased NTC expansion. On the contrary, there is 500 MW less NTC expansion between NO1 and Sweden in HEAT compared to BASE. This is because Sweden develops 8 GW less wind power, or an average decrease of 8 TWh/year, towards 2060 in HEAT compared to BASE, while wind power capacity in NO1 is the same. Consequently, electricity exports from Sweden are reduced in HEAT compared to BASE, and the required transmission capacity between Sweden and NO1 is reduced. Note that Norway as a whole develops 11 GW less wind in HEAT, or an average decrease of 13 TWh/year.

5.4. Flexibility in local energy communities

5.4.1. Heat converter and storage flexibility

There is significant capacity expansion of HWST in Norway in HEAT, where most expansion happen between 2030 and 2050. The heat storage is mostly utilized to balance the electricity use of electricity-to-heat converters. HWST are generally charged when Norwegian exports are decreased because that means electricity is available for heat conversion. The vice versa is also the case: HWST are generally discharged when exports are high because less electricity is available for heat conversion. In such a way, the central power system and the building heat systems are operated more cost efficiently through the flexibility provided by regulated hydropower, electricity-to-heat converters, and HWST. There is only capacity expansion of the ‘large’ HWST as it is a cheaper investment alternative (see Table 1). The new HWST storage capacity reaches 106 GWh for Norway in total by 2060, which would

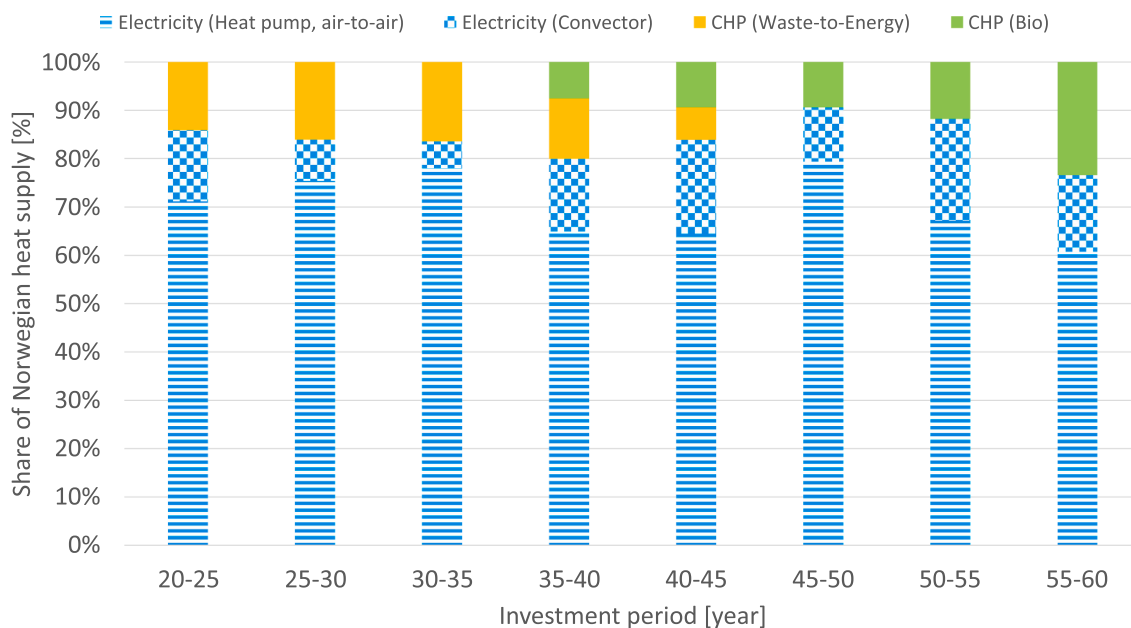


Fig. 6. Share of annual heat supply by technology in all Norwegian zones (NO1-NO5) from 2020 to 2060.

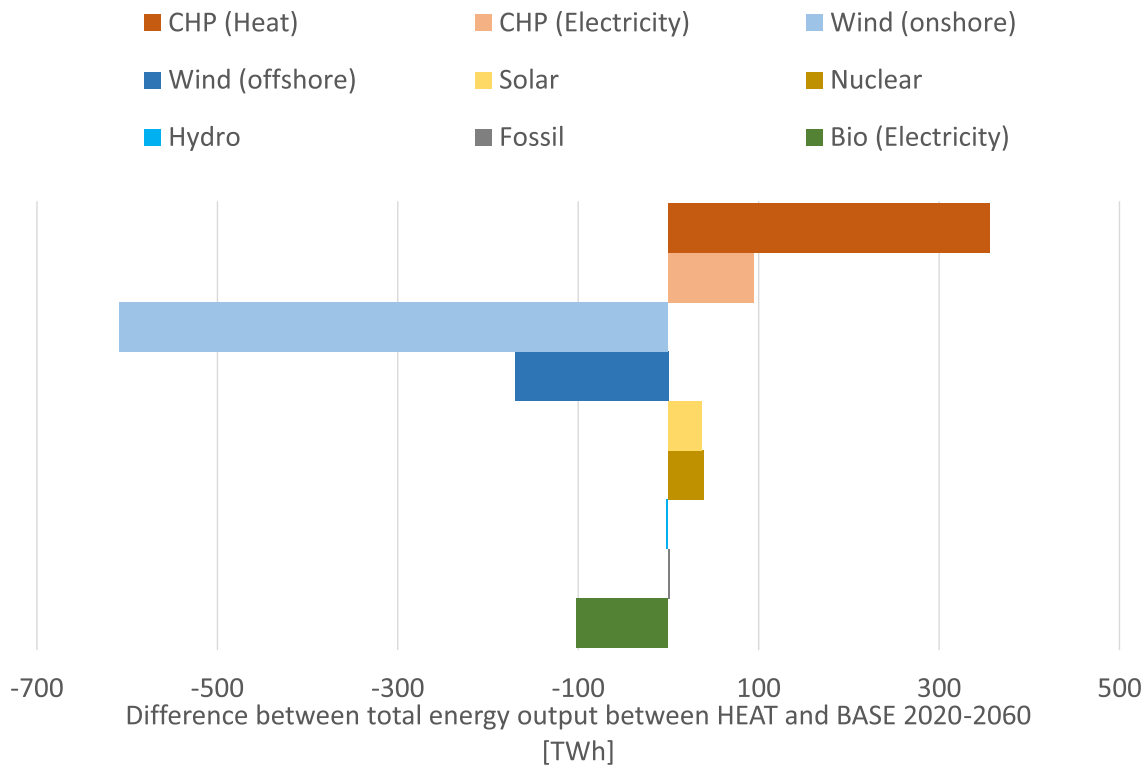


Fig. 7. Difference in total energy output from 2020 to 2060 by technology for all European countries in HEAT compared to BASE.

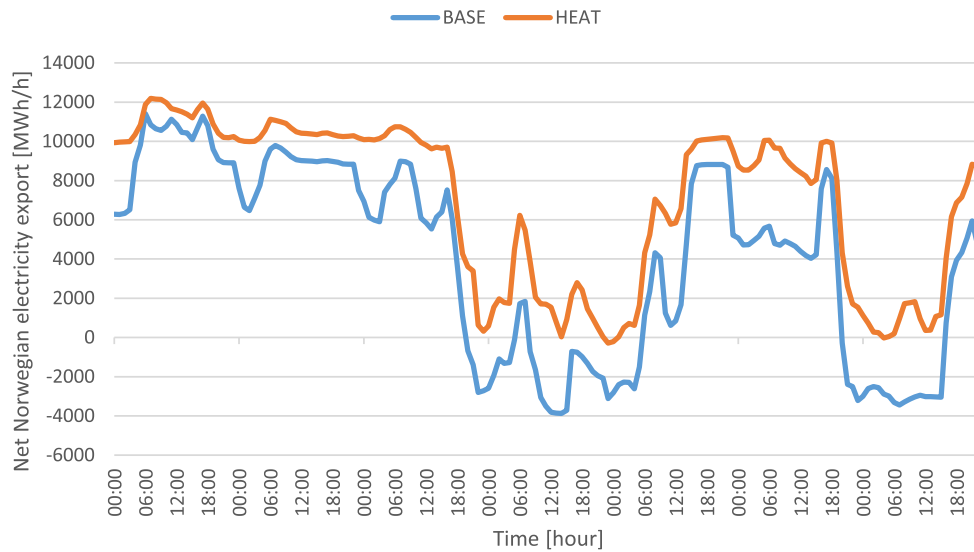


Fig. 8. Net hourly electricity export from Norway in the same fall week scenario for BASE and HEAT between 2030 and 2035. Negative values means net import to Norway.

require a total area⁴ of 32, 000-133, 000 m² [48].

5.4.2. Electric vehicle charging

The total capacity expansion of EV charging capacity in Norway sums up to 4.3 GW in BASE, and there is 3% less capacity expansion in HEAT compared to BASE. After 2040, there is less EV charging capacity developed in NO1 and NO2 in HEAT compared to BASE indicating that building heat flexibility can partly substitute the need for EV charging infrastructure used for flexibility purposes. In other words, increased

building heat flexibility increases the opportunity for peak shaving of EV charging profiles.

Load shifting, or optimal timing, of EV charging is increasingly valuable towards 2060 in both BASE and HEAT. Fig. 9 shows an example of one scenario for net charging of EVs in NO2 in a fall week in 2040–2045, and there is less variability in the EV charging in HEAT as the flexibility need is also met through smart building heating. Fig. 9 also shows a net V2G for NO2 in BASE, however, there is no net V2G for all Norwegian nodes in BASE or HEAT.

5.5. Discussion

The EMPIRE model's objective is to minimize total system costs subject

⁴ Assuming the space requirement for 'large' hot water tanks ranges from 0.3 m²/MWh to 1.25 m²/MWh [48]

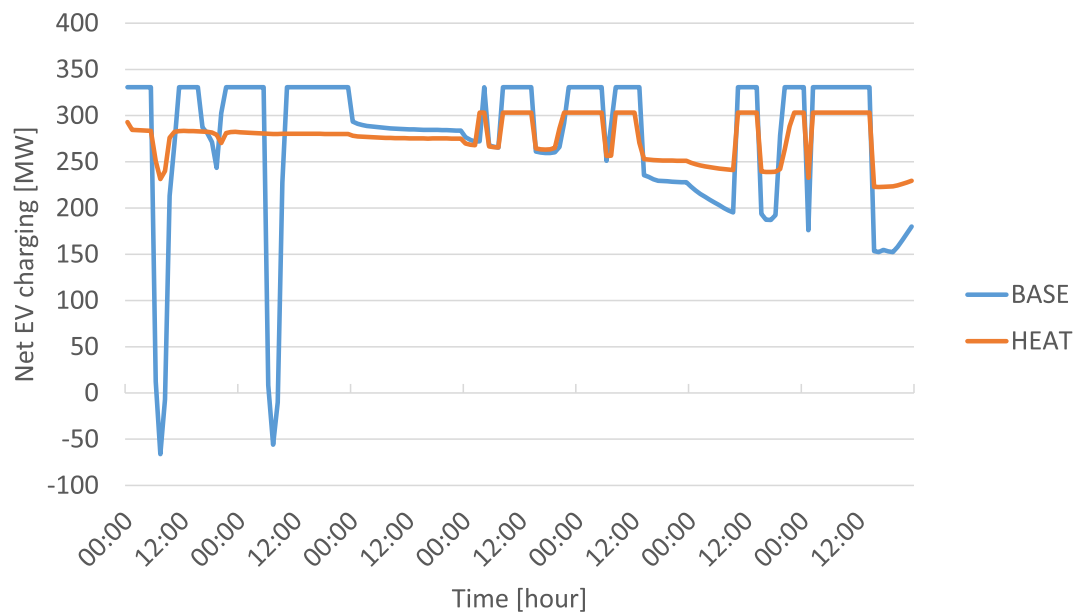


Fig. 9. Net charging of all EVs in NO2 in the same fall week in one stochastic scenario between 2040 and 2045.

to an ambitious European emission cap towards 2060. The output thus represents a simulation of the most cost-efficient decarbonization pathway for Europe as a whole, and does not represent the pathway of minimized emissions nor maximized energy efficiency. As emissions are capped, the difference in expected emissions from HEAT compared to BASE is small for Europe as a whole. However, there is a small increase in Norwegian emissions from WtE plants in HEAT compared to BASE, and this is fully compensated by a decrease in emissions for the rest of Europe in the critical scenarios. Although the increase in Norwegian emissions is small, these results demonstrate an important insight from our analysis: European emissions can cost-efficiently decrease even if national emissions for single European countries increase. This is especially relevant for Norway since Norwegian hydropower is valuable for VRES integration [19,20].

The case study of this paper is conducted within the European power market as we only analyze the development of Norwegian heat systems that are electric today. This is done to compare Norwegian heat system development when it is assumed to be an inflexible load (BASE) and when it can develop freely as building heating assets (HEAT). However, the whole heating market, as well as the gas market, is relevant to consider in multi-sector energy system analyses, especially when considering countries with less electric heating than Norway. Future work includes using the EMPIRE modeling framework to accommodate a larger share of the heating market and thus a larger opportunity for sector coupling.

The EMPIRE modeling framework assumes perfect coordination and resource aggregation within European countries and perfect competition between European countries. Therefore, the EMPIRE model inherently assumes that all energy resources within one node are coordinated, and that all flexibility assets in local energy communities can be provided on a national level within an hour, e.g. through an aggregator role [66]. This poses both technical, regulatory, and even social challenges [67]. Large-scale resource coordination calls for sophisticated metering and a close link between end-users and flexibility markets. Our modeling results indicate that if such coordination can be

successful, the utilization of flexible resources at the end-user level could impact the central power system, including capacity expansion of transmission and generation [68].

6. Conclusion

This paper extends the stochastic linear programming model EMPIRE to study sector coupling between the central power system, heat systems in buildings, and flexible charging of EVs under uncertainty of VRES availability, heat pump COP, load, and EV demand. We apply the updated model to a European case study where we analyze decarbonization under uncertainty with and without sector coupling between the central power system and Norwegian building heat systems. Results from our case study indicate that a growth in non-electric heat supply to buildings in Norway is attractive for Europe towards 2060, and that the greatest share of building heat demand should be met with electric building heat solutions dominated by heat pumps coupled with heat storage. The integrated development of the European power system and Norwegian building heat systems increase export of hydropower from Norway to neighbouring countries. More work is needed to realistically represent the uncertain availability and costs related to aggregated local resources like heat systems and EVs. Future work also includes considering building heat and EVs for several European countries to study cost-efficient interactions between building heat systems, electric mobility systems, and the central power system while meeting decarbonization targets.

CRedit authorship contribution statement

Stian Backe: Conceptualization, Methodology, Software, Validation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. **Magnus Korpås:** Conceptualization, Funding acquisition, Supervision, Writing - review & editing. **Asgeir Tomasgard:** Conceptualization, Funding acquisition, Supervision, Writing - review & editing.

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.

Appendix A. Nomenclature of EMPIRE

A.1. Sets

- \mathcal{G} Set of possible generator types,
- \mathcal{B} Set of possible storage types,
- \mathcal{R} Set of possible electricity-to-heat converter types,
- $I = \{1, 2, \dots, |I|\}$ Set of investment periods,
- $\mathcal{H} = \{1, 2, \dots, |\mathcal{H}|\}$ Set of operational periods,
- S Set of seasons,
- \mathcal{N} Set of nodes,
- $\mathcal{A} \subset \mathcal{N} \times \mathcal{N}$ Set of unidirectional interconnectors,
- $\mathcal{L} \subset \mathcal{A}$ Set of bidirectional interconnectors,
- Ω Set of scenarios,
- $\mathcal{G}_{EL} \subset \mathcal{G}$ Set of possible electricity generator types,
- $\mathcal{G}_{HT} \subset \mathcal{G}$ Set of possible building heat generator types,
- $\mathcal{G}_n \subset \mathcal{G}$ Set of possible generator types in node $n \in \mathcal{N}$,
- $\mathcal{G}^{\text{Ramp}} \subset \mathcal{G}$ Set of generator types limited by ramping,
- $\mathcal{G}^{\text{RegHyd}} \subset \mathcal{G}$ Set of regulated hydro generator types,
- $\mathcal{G}^{\text{Hyd}} \subset \mathcal{G}$ Set of all hydro generator types,
- $\mathcal{B}_{EL} \subset \mathcal{B}$ Set of possible electricity storage types,
- $\mathcal{B}_{HT} \subset \mathcal{B}$ Set of possible heat storage types,
- $\mathcal{B}_{FX} \subset \mathcal{B}_{EL}$ Set of flexible electricity demand,
- $\mathcal{B}_n \subset \mathcal{B}$ Set of possible storage types in node $n \in \mathcal{N}$,
- $\mathcal{B}^\dagger \subset \mathcal{B}$ Set of storage types with fixed energy and charging ratio,
- $\mathcal{R}_n \subset \mathcal{R}$ Set of available electricity-to-heat converters in node $n \in \mathcal{N}$,
- $\mathcal{H}_s = \{h_s^1, h_s^2, \dots, |\mathcal{H}_s|\} \subset \mathcal{H}$ Set of operational periods in season $s \in S$,
- $\mathcal{A}_n^{\text{in}} \subset \mathcal{N} \times \mathcal{N}$ Set of arcs flowing into node $n \in \mathcal{N}$,
- $\mathcal{A}_n^{\text{out}} \subset \mathcal{N} \times \mathcal{N}$ Set of arcs flowing out from node $n \in \mathcal{N}$.

A.2. Input data

A.2.1. Costs

- $c_{a,i}^{\text{node}}$: Investment cost of asset $a \in \mathcal{G} \cup \mathcal{B} \cup \mathcal{R}$ in period $i \in I$,
- $c_{b,i}^{\text{storCH}}$: Investment cost of charging of storage $b \in \mathcal{B}$ in period $i \in I$,
- $c_{n_1, n_2, i}^{\text{tran}}$: Investment cost of bidirectional interconnection $(n_1, n_2) \in \mathcal{L}$ in period $i \in I$,
- $q_{g,i}^{\text{gen}}$: Operational cost of generator type $g \in \mathcal{G}$ in period $i \in I$,
- $q_{g,i}^{\text{CO}_2}$: CO₂ emission factor of generator type $g \in \mathcal{G}$ in period $i \in I$,
- $q_{n,i}^{\text{ll, EL}}$: Value of lost electric specific load in node $n \in \mathcal{N}$ in period $i \in I$,
- $q_{n,i}^{\text{ll, HT}}$: Value of lost building heat load in node $n \in \mathcal{N}$ in period $i \in I$,
- $Q_i^{\text{CO}_2}$: CO₂ emission ceiling for all generators in period $i \in I$.

Acknowledgement

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A.2.2. Technology limitations

- i_a^{life} : Lifetime of investment in asset $a \in \mathcal{G} \cup \mathcal{B} \cup \mathcal{L} \cup \mathcal{R}$,
 γ_g : Ramping factor for generator type $g \in \mathcal{G}_{\text{Ramp}}$,
 $\eta_{n_1, n_2}^{\text{tran}}$: Efficiency factor for transmission losses along arc $(n_1, n_2) \in \mathcal{A}$, $\eta_{n_1, n_2}^{\text{tran}} \in (0, 1)$,
 η_b^{chrg} : Efficiency factor for charge losses with storage type $b \in \mathcal{B}$, $\eta_b^{\text{chrg}} \in (0, 1)$,
 η_b^{dischrg} : Efficiency factor for discharge losses with storage type $b \in \mathcal{B}$, $\eta_b^{\text{dischrg}} \in (0, 1)$,
 η_b^{bleed} : Efficiency factor for bleed losses with storage type $b \in \mathcal{B}$, $\eta_b^{\text{bleed}} \in (0, 1)$,
 ρ_b : Capacity ratio between charge/discharge speed for storage type $b \in \mathcal{B}$,
 β_g^{CHP} : Share of electric output per heat output from CHP generator $g \in \mathcal{G}_{\text{EL}}$,
 $\forall g \notin \mathcal{G}_{\text{EL}} \cap \mathcal{G}_{\text{HT}}: \beta_g^{\text{CHP}} = 1$,
 β_b^{stor} : Ratio between charging and energy capacity for storage type $b \in \mathcal{B}^{\dagger} \subseteq \mathcal{B}$,
 κ_b : Share of installed energy capacity initially available in storage type $b \in \mathcal{B}$
in each representative time period,
 ξ_n^{HydLim} : Max expected annual output from total hydro in node $n \in \mathcal{N}$,
 $\bar{x}_{a, n, i}^{\text{node}}$: Initial capacity of nodal asset $a \in \mathcal{G}_n \cup \mathcal{B}_n \cup \mathcal{R}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
 $\bar{x}_{b, n, i}^{\text{storCH}}$: Initial capacity of charging of storage $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
 $\bar{x}_{n_1, n_2, i}^{\text{tran}}$: Initial capacity of bidirectional interconnection $(n_1, n_2) \in \mathcal{L}$ in period $i \in \mathcal{I}$,
 $\bar{X}_{a, n, i}^{\text{node}}$: Max investments in nodal asset $a \in \mathcal{G}_n \cup \mathcal{B}_n \cup \mathcal{R}_n$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
 $\bar{X}_{b, n, i}^{\text{storCH}}$: Max investments in charging of storage $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
 $\bar{X}_{n_1, n_2, i}^{\text{tran}}$: Max investments in bidirectional interconnection $(n_1, n_2) \in \mathcal{L}$ in period $i \in \mathcal{I}$,
 $\bar{V}_{a, n, i}^{\text{node}}$: Max installed capacity of asset $a \in \mathcal{G}_n \cup \mathcal{B}_n \cup \mathcal{R}_n$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
 $\bar{V}_{b, n, i}^{\text{storCH}}$: Max installed capacity of storage of charging $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ and period $i \in \mathcal{I}$,
 $\bar{V}_{n_1, n_2, i}^{\text{tran}}$: Max installed capacity of bidirectional interconnection $(n_1, n_2) \in \mathcal{L}$ in period $i \in \mathcal{I}$.

A.2.3. Scenario input

- π_ω : Probability of scenario $\omega \in \Omega$,
 $\xi_{g, n, h, i, \omega}^{\text{gen}}$: Availability of generator type $g \in \mathcal{G}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$
and scenario $\omega \in \Omega$,
 $\xi_{n, h, i, \omega}^{\text{load}}$: Electric specific load in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,
 $\xi_{n, h, i, \omega}^{\text{load, HT}}$: Building heat load in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,
 $\xi_{n, s, i, \omega}^{\text{RegHydLim}}$: Max output from regulated hydro in node $n \in \mathcal{N}$ in $s \in \mathcal{S}$, $i \in \mathcal{I}$ and $\omega \in \Omega$,
 $\eta_{n, r, h, i, \omega}^{\text{E2H}}$: Efficiency factor for electricity-to-heat converter $r \in \mathcal{R}$ in node $n \in \mathcal{N}$
in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,
 $\xi_{n, b, h, i, \omega}^{\text{FX}}$: Energy required by $b \in \mathcal{B}_{\text{FX}}$ in $n \in \mathcal{N}$ by hour $h \in \mathcal{H}$ in $i \in \mathcal{I}$ and $\omega \in \Omega$.
($\xi_{n, h, i, \omega}^{\text{load}}$ is subtracted by the hourly average requirement for each season).

A.3. Variables

A.3.1. Investment decision variables

- $0 \leq x_{a, n, i}^{\text{node}} \leq \bar{X}_{a, n, i}^{\text{node}}$: Investments in asset $a \in \mathcal{G}_n \cup \mathcal{B}_n \cup \mathcal{R}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
 $0 \leq x_{b, n, i}^{\text{storCH}} \leq \bar{X}_{b, n, i}^{\text{storCH}}$: Investments in charging of storage $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
 $0 \leq x_{n_1, n_2, i}^{\text{tran}} \leq \bar{X}_{n_1, n_2, i}^{\text{tran}}$: Investments in bidirectional interconnection $(n_1, n_2) \in \mathcal{L}$ in period $i \in \mathcal{I}$,
 $0 \leq v_{a, n, i}^{\text{node}} \leq \bar{V}_{a, n, i}^{\text{node}}$: Capacity of asset $a \in \mathcal{G}_n \cup \mathcal{B}_n \cup \mathcal{R}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
 $0 \leq v_{b, n, i}^{\text{storCH}} \leq \bar{V}_{b, n, i}^{\text{storCH}}$: Capacity of charging of storage $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $i \in \mathcal{I}$,
 $0 \leq v_{n_1, n_2, i}^{\text{tran}} \leq \bar{V}_{n_1, n_2, i}^{\text{tran}}$: Capacity of bidirectional interconnection $(n_1, n_2) \in \mathcal{L}$ in period $i \in \mathcal{I}$.

A.3.2. Operational decision variables

- $0 \leq y_{g,n,h,i,\omega}^{\text{gen}} \leq \xi_{g,n,h,i,\omega}^{\text{gen}} v_{g,n,i}^{\text{node}}$: Output by generator type $g \in \mathcal{G}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,
- $0 \leq y_{n_1,n_2,h,i,\omega}^{\text{tran}} \leq v_{n_1,n_2,i}^{\text{tran}} \vee v_{n_2,n_1,i}^{\text{tran}}$: Electricity transmission from node $n_1 \in \mathcal{N}$ to $n_2 \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$, $(n_1, n_2) \in \mathcal{A}$,
- $0 \leq y_{b,n,h,i,\omega}^{\text{chrg}} \leq v_{b,n,i}^{\text{storCH}}$: Charging of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$, and scenario $\omega \in \Omega$,
- $0 \leq y_{b,n,h,i,\omega}^{\text{dischrg}} \leq v_{b,n,i}^{\text{storCH}}$: Discharging of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$, and scenario $\omega \in \Omega$,
- $0 \leq w_{b,n,h,i,\omega}^{\text{stor}} \leq v_{b,n,i}^{\text{node}}$: Energy content of storage type $b \in \mathcal{B}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,
- $0 \leq y_{r,n,h,i,\omega}^{\text{E2H}} \leq v_{r,n,i}^{\text{node}}$: Electricity-to-heat conversion by converter type $r \in \mathcal{R}_n$ in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,
- $0 \leq y_{n,h,i,\omega}^{\text{ll,EL}} \leq +\infty$: Electric specific load shed in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$,
- $0 \leq y_{n,h,i,\omega}^{\text{ll,HT}} \leq +\infty$: Building heat load shed in node $n \in \mathcal{N}$ in period $h \in \mathcal{H}$, $i \in \mathcal{I}$ and scenario $\omega \in \Omega$.

Appendix B. Technology input data

Tables 3 and 4

Table 3

Electricity generator investment options and their assumed capital costs (in €/kW) for future periods. Source: [49].

| Technology | Capital cost [€/kW] | | |
|---------------------------------|---------------------|---------|---------|
| | '20-'30 | '35-'40 | '45-'60 |
| Lignite (conventional) | 1800 | 1800 | 1800 |
| Oil (conventional) ^a | – | – | – |
| Coal (conventional) | 1600 | 1600 | 1600 |
| Coal (10% bio co-fire) | 1600 | 1600 | 1600 |
| Combined Cycle Gas | 720 | 690 | 660 |
| Open Cycle Gas | 400 | 400 | 400 |
| Nuclear | 6000 | 6000 | 6000 |
| Bio (conventional) | 2000 | 1800 | 1700 |
| Geothermal | 4970 | 4586 | 3749 |
| Hydro (regulated) | 3000 | 3000 | 3000 |
| Hydro (run-of-river) | 2450 | 2400 | 2350 |
| Solar Photovoltaic | 710 | 663 | 519 |
| Waste (electricity-only) | 2030 | 2013 | 2005 |
| Wave | 6100 | 3100 | 2025 |
| Wind (offshore) | 2778 | 2048 | 1929 |
| Wind (onshore) | 1295 | 1161 | 1010 |

^a 'Oil (conventional)' is not considered an investment option, only an existing power generator.

Table 4

Electricity storage investment options and their assumed capital costs for future periods. Source: [69,70].

| Technology | Capital cost [€/kW] | |
|------------------------|---------------------|----------------|
| | Charge | Storage |
| Hydro (pumped storage) | 1000 | 100 |
| Lithium-ion Battery | 198 ^a | 0 ^b |

^a Capital charge cost is €246/kW for the first investment period (2020 to 2025).

^b Charge and storage capacity are developed together for lithium-ion batteries, hence no capital storage costs.

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