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The impacts of the electricity demand pattern on electricity system cost and the electricity supply mix: A comprehensive modeling analysis for Europe

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A B S T R A C T

Energy system models for long-term planning are widely used to explore the future electricity system. Typically, to represent the future electricity demand in these models, historical demand profiles are used directly or scaled up linearly. Although the volume change for the electricity demand is considered, the potential change of the demand pattern is ignored. Meanwhile, the future electricity demand pattern is highly uncertain due to various factors, including climate change, e-mobility, electric heating, and electric cooling. We use a techno-economic cost optimization model to investigate a stylized case and assess the effects on system cost and electricity supply mix of assuming different demand patterns for the models. Our results show that differences in diurnal demand patterns affect the system cost by less than 3%. Similarly, demand profiles with a flat seasonal variation or a winter peak result in only minor changes in system cost, as compared to the present demand profile. Demand profiles with a summer peak may display a system cost increase of up to 8%, whereas the electricity supply mix may differ by a factor of two. A more detailed case study is conducted for Europe and the results are consistent with the findings from the stylized case.

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1. Introduction

Energy system models for long-term investment planning are widely used to generate insights for policy analysis and decision making for the future electricity system. Such models typically minimize total system costs under technological, environmental and policy constraints and generate a cost-effective electricity system portfolio. Often, perfect foresight with regard to the future technology costs, resource availability, and electricity demand is assumed. However, these models have been criticized for their inability to capture the uncertainties surrounding the future electricity system [1–4]. With large uncertainties that grow over time, singular projections in energy system models often fall short of the full spectrum of the plausible future electricity system and produce misleading results. Currently, there is a growing body of studies addressing the uncertainties associated with technological, economic, and societal parameters. These studies relate to future technology investment costs [5], weather conditions [6,7], discount rates [8], policies [9], and indeed, demand growth [10,11]. Many studies focusing on the future electricity demand have either directly used the historical demand profile or have linearly scaled up the historical demand profile to a new value as the future electricity demand [12–16]. Although the volume of annual electricity demand is considered, the inter-temporal pattern of the electricity demand profile (demand pattern) is assumed to remain the same.

It is well established in the literature that both the volume of annual electricity demand and the demand pattern are heavily influenced by factors such as population expansion, economic growth, climate change, e-mobility, electric heating (EH), electric cooling (EC), and technological innovations [10,11,17–21]. Specifically, some recent studies have highlighted the impacts of electric vehicles (EVs), EH and EC on the demand pattern. Boßmann and Staffell [10] estimated that the peak demand in the UK would increase by 50% due to the extensive diffusion of EVs and EH by 2050. A slightly milder, but still large, increase of 28% for the peak demand due to the wide adoption of EVs and EH in the UK was found by Pudjianto et al. [19] under the condition that demand-side

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management (DSM) is implemented. Staffell and Pfenninger [11] estimated a 20% increase in peak demand around 2030 in the UK due to EH only. Kannan [20] found that the summer peak in Switzerland would increase by 2%–23% in 2050 due to increased use of air conditioners (ACs). These studies underline the substantial uncertainties regarding the future electricity demand pattern.

Some studies have estimated that radical changes in the electricity demand pattern may strongly affect the electricity system [10,11,19]. The impacts might be more evident for a renewable electricity system as it is less capable of load following due to the intermittency of variable renewable energy (VRE) resources, as compared with the conventional electricity system based on dispatchable thermal power plants [22]. Therefore, given the high level of uncertainty regarding the future electricity demand pattern, it is important to understand how the changes in the electricity demand profile affect the modeling results, particularly in terms of the electricity supply mix and the system cost for the renewable electricity system. Several studies [4,23,24] have already evaluated the impacts of the volume change for the annual electricity demand on the electricity system, and found that a higher electricity demand might lead to more investment in renewable energy and a higher electricity cost. Even though several analyses have suggested that the electricity demand pattern may change rather dramatically in the coming decades, only two studies [24,25] have explicitly analyzed the impacts of changes in the demand pattern on the electricity system. Zappa et al. [24] evaluated the impacts of different diurnal variations of the electricity demand on the level of investment in a renewable European electricity system using an optimization approach. They found that a higher diurnal variation leads to a slightly higher level of electricity generation due to more curtailment, whereas the impact on system cost is minor. Likewise, Boßmann et al. [25] analyzed the change in diurnal variation of the electricity demand and showed that a higher diurnal variation results in more investment in dispatchable generation capacities to deal with the peak demand, and slightly increases the electricity generation.

Some other studies have adopted cost optimization models to evaluate the impacts of DSM on the system cost and the composition of the electricity system with high penetration of renewables. Behboodi et al. [26] discovered that different DSM-related flexibilities (0%–10% of the hourly electricity demand) exert only a minor influence on the system cost. Similarly, Domínguez and Carrión [27] showed that DSM has weak impacts on investments in generation capacity and on the system cost, though it has a noticeable effect on system operation. Taljegard et al. [28] assessed EVs as a variation management strategy for the electricity system and reported that optimized charging of EVs slightly reduces the system cost compared to direct charging based on the owners' driving patterns.

The literature on DSM thus suggests that the shifting and curtailment of demand have limited impacts on electricity system cost, and this may be due to a limited potential (only a minor share of the load is shifted and curtailed in a short temporal duration) or high implementation costs. Still, future changes in the electricity demand patterns are unlikely to be limited to minor changes in the diurnal variation but may also entail large changes in diurnal variation (for example due to EV charging) and seasonal variation (for example due to EH and EC). It remains unknown as to how these potential changes in diurnal and seasonal demand patterns might affect the cost and supply mix of the future electricity system. Therefore, it is not clear whether or not the practice of using (scaled-up) historical electricity demand profiles in energy system models produces potentially unacceptable errors regarding the system cost and electricity supply mix. In the present study, we fill this gap in the knowledge and evaluate the conditions under which the demand pattern is important for the modeling results. Specifically, we address the following question: *What is the effect on the system cost and the electricity supply mix from applying different demand patterns in energy system models?*

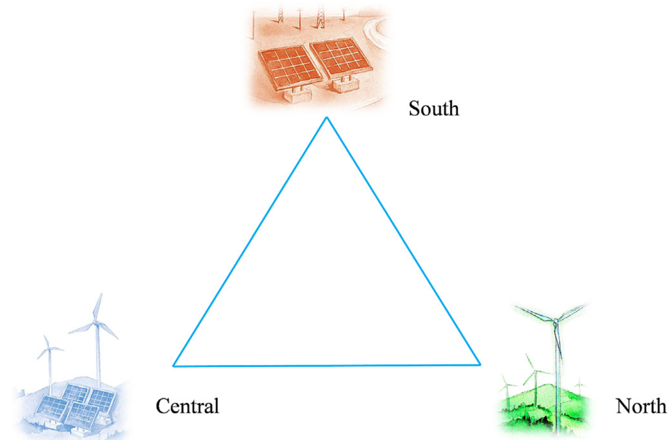

Fig. 1. Regions covered in the stylized case. We select three regions with typical VRE resource potentials and connect them with transmission grids to analyze the impacts of the demand pattern on an interconnected electricity system.

By investigating this question, we aim at providing insights regarding whether or not the changes in the future demand pattern can be disregarded for energy system modeling practice. To resolve this question, we use techno-economic cost optimization models for the electricity system to investigate a stylized case[1] involving three regions in Europe and one full-scale applied case (Europe). The paper is organized as follows. The model and input data are introduced in Section 2. In Section 3, the modeling results are presented. The mechanisms behind the results are then discussed in Section 4, and conclusions are drawn in Section 5. The model-specific code, input data, and output data are available online to ensure the transparency and reproducibility of the results [29].

2. Methods

In the first stage of the present study, a stylized case that involves three regions with VRE resource endowments typical for Europe (Fig. 1) is investigated with a simple cost optimization model. The three regions are located in the south, central and north of Europe respectively and they are named as: South, Central and North. Region South is provided with data for VRE resources and electricity demand pattern from Spain plus Portugal. Similarly, data for VRE resources and electricity demand patterns for Germany and Norway are assigned to region Central and North respectively. The reason why we investigate a simplified stylized case is to look at regions with typical VRE resource potentials, to explore numerous possible demand patterns while keeping a reasonable computation time, and to make the results easy to analyze. Region South has good solar resources and region North is characterized by good wind resources. Region Central displays both solar and wind resources, yet neither as good as those in South or North, see Fig. 2. Since our main purpose is to analyze the impact of the demand pattern on an interconnected electricity system, there is the option

[1] The stylized case refers to a stylized set-up for the electricity demand profiles. It has several different scenarios depending on the specific shape of the electricity demand profiles.

to invest in transmission connections between the three nodes. The interrelated electricity system in the stylized case is modeled for one year with an hourly time resolution, given a cap on CO_2 emission expressed in grams of CO_2 per kWh of electricity demand. The effects of different demand patterns on the system cost and electricity supply mix are analyzed. In order to validate the results obtained from the stylized case, the REX model [30] is used to evaluate the European electricity system, by comparing scenarios with different demand patterns.

2.1. The energy system model for the stylized case

The model developed for the stylized case is a greenfield cost optimization model for capacity investments and the dispatch of electricity generation, transmission and storage. It employs an overnight investment approach to identify the minimum cost portfolio for the future electricity system. This entails a linear optimization problem with the objective to minimize the total annual electricity system cost, given the constraints of meeting the electricity demand, the renewable energy resource potentials, and a CO_2 emission cap. An overview of the model, the generation technology options, and the variation management strategies are depicted in Fig. 3.

The nodes in the model are labeled by r, n represents the electricity generation technology at the node, m represents the demand-response at the node, and t is the time of the year. The total annual system cost consists of fixed annualized costs C_n for electricity generation capacity G_{rn}, fixed annualized costs $C^{storage}$ for storage S_r, fixed annualized costs $C_{rr'}$ for transmission capacity $Z_{rr'}$, variable costs R_n for electricity generation g_{rnt} and variable costs R_m for demand-response d_{rmt}. For storage and transmission, the variable cost is assumed to be zero. Therefore, the objective function of this linear optimization problem is formulated as follows:

$$Min \sum_{r,n} C_n G_{rn} + \sum_{r} C^{storage} S_r + \sum_{r,r'} 0.5 C_{rr'} Z_{rr'} + \sum_{r,n,t} R_n g_{rnt} + \sum_{r,m,t} R_m d_{rmt}. \tag{1}$$

Since $Z_{rr'}$ and $Z_{r'r}$ represent the capacity for the same transmission line rr', a coefficient of 0.5 is incorporated into the transmission cost formula to avoid double counting.

The electricity demand has to be satisfied through generation, demand-response, trade and storage.

$$\sum_{n} g_{rnt} + \sum_{m} d_{rmt} + \sum_{r'} (\eta_\gamma \gamma_{r'rt} - \gamma_{rr't}) + (\eta_s \alpha_{rt} - \beta_{rt}) \geq D_{rt}\ , \tag{2}$$

where g_{rnt} is the electricity generation, d_{rmt} is the demand-response, $\gamma_{rr't}$ is the electricity traded from node r to node r', η_γ is the efficiency of transmission, α_{rt} is the discharge from storage, β_{rt} is the charge into storage, η_s is the round-trip efficiency of storage and D_{rt} is the hourly electricity demand.

For the other constraints imposed on the optimization problem and a more detailed description of the model, please see Appendix

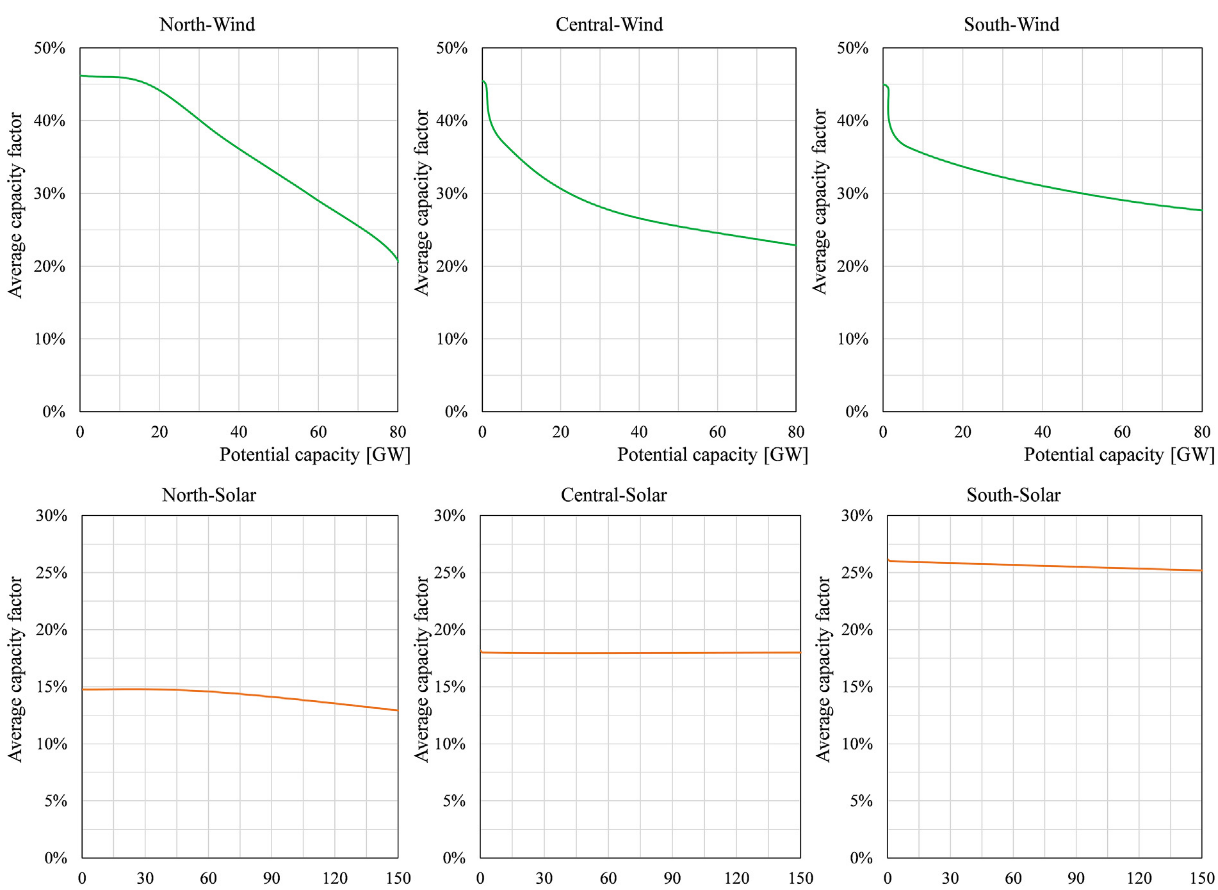

Fig. 2. Resource endowments for wind and solar in each region for the stylized case. The average capacity factor refers to the average hourly capacity factor for wind and solar in one year. All the data are collected through the GIS model developed by Mattsson et al. [31].

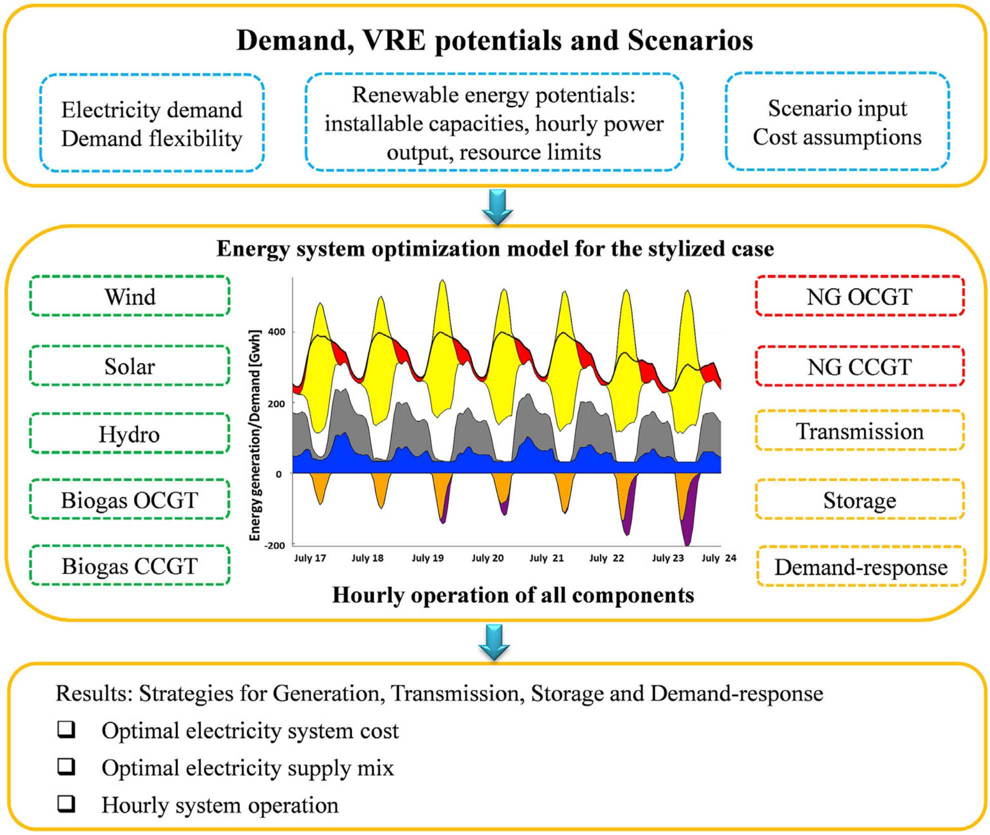

Fig. 3. Overview of the model for the stylized case. OCGT refers to open-cycle gas turbine; CCGT refers to combined-cycle gas turbine; NG refers to natural gas. The input data are shown in the blue dashed box. The renewable generation technologies are listed in the green dashed box. The fossil fuel fired generation technologies are presented in the red dashed box and variation management strategies are included in the orange dashed box. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

B in the supplementary material.

2.2. Demand data and scenarios for the stylized case

The electricity demand data for the three regions are taken from ENTSO-E [32], and they are scaled down to the same value 87 TWh (the average electricity demand in 2014 for European countries). We adopt a lower electricity demand for each region because in a renewable electricity system, scarcity of supply may occur when there is a high electricity demand and restricted land availability for VRE, and this strongly influences the modeling results [33]. A lower electricity demand can mitigate the impacts of land use constraints on the modeling results and can reveal more clearly the impacts of different electricity demand patterns. The demand profiles are then manipulated so as to display typical, stylized seasonal and diurnal variations (see Fig. 4). We do not make a detailed estimation of all the possible future demand patterns. Still, the stylized demand patterns created in this study do represent the typical possible future electricity demand profiles with regard to the potentials for EV charging, EH, EC, etc. By applying these typical demand profiles as input to the model and contrasting the modeling results, we are then able to evaluate the magnitude of error in modeling results if the historical demand profile is scaled up as input to the model. The stylized seasonal variations for the demand profile consist of the following six types:

1. Current demand pattern (N), whereby the demand profile is maintained in its current shape (Fig. 4a–c);
2. Zero seasonal variation (A), such that there is no seasonal variation for the demand profile (Fig. 4d–f);
3. Medium winter peak (W), whereby the annual peak demand (the maximum electricity demand in 1 year) is in the wintertime and the seasonal variation (the maximum peak demand in winter minus the minimum peak demand in summer) is 20% of the annual peak demand (Fig. 4g);
4. High winter peak (W+), whereby the annual peak demand is in the wintertime and the seasonal variation is 40% of the annual peak demand (Fig. 4h);
5. Medium summer peak (S), such that the annual peak demand is in the summertime and the seasonal variation (the maximum peak demand in summer minus the minimum peak demand in winter) is 20% of the annual peak demand (Fig. 4i); and
6. High summer peak (S+), whereby the annual peak demand is in the summertime and the seasonal variation is 40% of the annual peak demand (Fig. 4j).

There are three types of stylized diurnal variations for the demand profile:

1. Zero diurnal variation (Zero) (Fig. 4d);
2. Medium diurnal variation (Medium), such that the diurnal variation (the maximum electricity demand minus the minimum electricity demand in 1 day) is 25% of the daily peak demand (maximum electricity demand in 1 day) (Fig. 4e); and
3. High diurnal variation (High), whereby the diurnal variation is 45% of the daily peak demand (Fig. 4f).

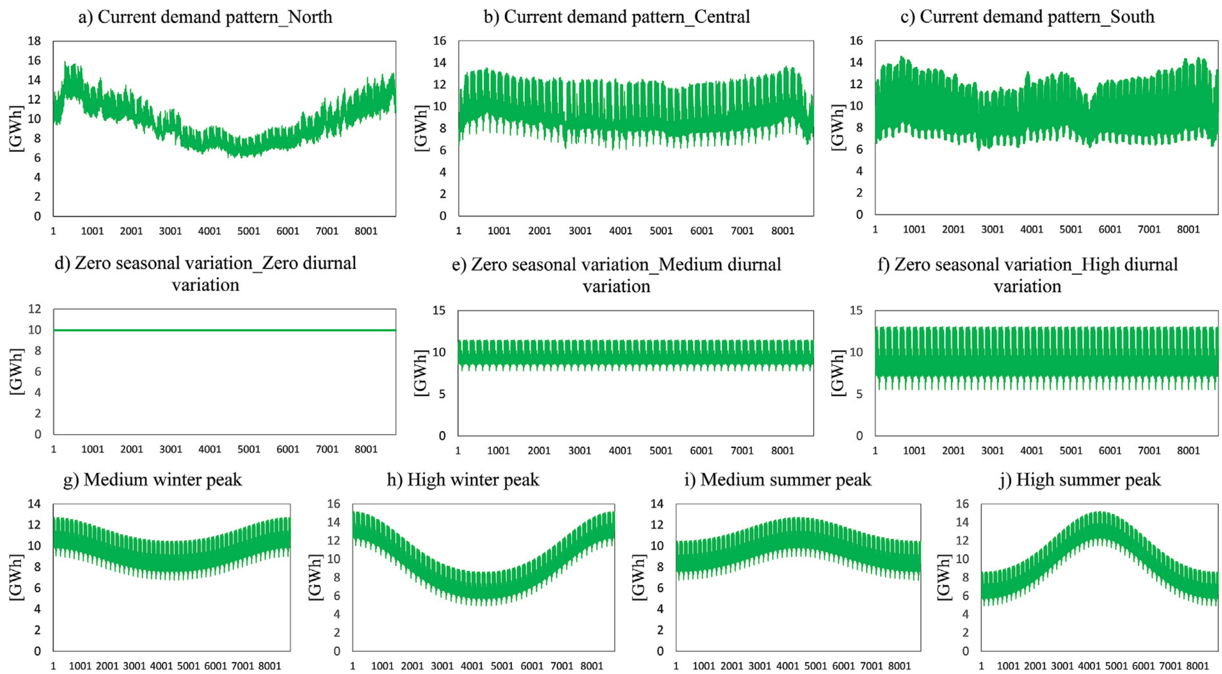

Fig. 4. Different electricity demand patterns in the stylized case.

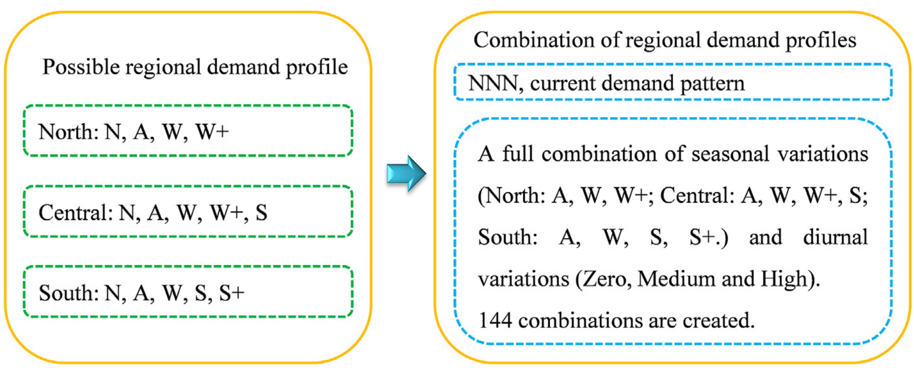

Fig. 5. Demand profile for each region and the combinations of the three regional demand profiles. The possible electricity demand profiles for each region are presented in the green dashed box and the combinations are shown in the blue dashed box. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Considering the climate situation in each region and that the seasonal variation is mainly due to heating/cooling, the summer peak (S, S+) is excluded for region North, the high summer peak (S+) is excluded for region Central, and the high winter peak (W+) is excluded for region South. All the other demand patterns for each region are regarded as the possible future demand patterns for these three regions and they are shown in Fig. 5. The demand data input to the optimization model are combinations of seasonal and diurnal variations of the electricity demand profiles for the three regions. In total there are 145 combinations. These combinations are categorized according to the shape of the aggregated demand profile[2] into six Groups labeled *Current demand pattern*, *Zero seasonal variation*, *Medium winter peak*, *High winter peak*, *Medium summer peak*, and *High summer peak*. Each combination is one Scenario and there could be several different combinations (Scenarios) in each Group. For the Group of the *Current demand pattern*, there is only one Scenario, with the three regions North, Central and South maintaining the current demand pattern (NNN). The Scenario of the *Current demand pattern* is the base Scenario for this study. The Scenarios in the other five Groups display three different diurnal variations (*Zero*, *Medium*, *High*) depending on the shape of the aggregated demand profile. An overview of the Scenarios for the stylized case is given in Table 1.

2.3. Input data for the stylized case

In this study, the transmission grids are assumed to be high-voltage direct current (HVDC) connections and the trade in electricity is represented as a simple transport problem [15,16]. The length of the transmission line is measured as the distance between

[2] Under each combination of seasonal and diurnal variations of the three regional demand profiles, if we sum the hourly electricity demand for the three regions, we get an aggregated demand profile. We categorize the different combinations based on the shape of the aggregated demand profile. The aggregated demand profile is used as a benchmark to define scenarios for the present study. It is not the input demand data for the model. The three regional demand profiles are the input to the model.

Table 1
Scenarios for the stylized case.

Scenario[a]	Seasonal Variation	Diurnal variation	Detailed combination[b] (Sequence: North, Central, South)
Current demand pattern	Current pattern	Current pattern	NNN
Zero seasonal variation	Zero	Zero/ Medium/ High	AAA, ASW, AWS, WAS, WSA, AW+S+, W+AS+
Medium winter peak	<20% of annual peak demand, winter peak	Zero/ Medium/ High	W+SS, AAW, AWA, WAA, WWS, WSW, WW+S+, W+WS+, AW+S, W+AS, W+SA, AWW, WWA, WAW, AW+A, W+AA, WW+S, W+WS, W+SW, W+W+S+
High winter peak	≥20% of annual peak demand, winter peak	Zero/ Medium/ High	WWW, WW+A, AW+W, W+AW, W+WA, W+W+S, W+W+A, WW+W, W+WW, W+W+W
Medium summer peak	<14% of annual peak demand, summer peak	Zero/ Medium/ High	WWS+, ASA, AAS, WSS, W+SS+, AWS+, WAS+
High summer peak	≥14% of annual peak demand, summer peak	Zero/ Medium/ High	ASS, AAS+, WSS+, ASS+

[a] Each Scenario represents a combination of seasonal and diurnal variations of the demand profiles for the three regions. All the combinations are categorized into six Scenario Groups based on the shape of the aggregated demand profile. Different combinations might result in a similar shape for the aggregated demand profile. Therefore, inside each Scenario Group, there are several different detailed combinations.
[b] For each detailed combination other than NNN, the three regional demand profiles have the same diurnal variation and the amplitude of the diurnal variation has three levels: *Zero*, *Medium* and *High*.

the population center of each region [31]. All the sub-regions in the model are treated as "copper plates" without intra-regional transmission constraints. The cost for the battery is used as a reference for storage in the model. However, the storage option could be any other storage technology with a similar cost structure.

The capacities of reservoir hydropower (hydro reservoir) and run-of-river hydropower (hydro RoR) are based on a previous report [34], and, to match the down scaling of the electricity demand in each region, the values are scaled down to 2.2 GW and 1.4 GW respectively. The hydro inflow is taken from Ref. [15] and scaled down so that the contribution of hydropower is 10% of the annual electricity demand in each region. In order to consider the downstream ecosystem and human needs for water, the minimum environmental flow [35,36] of a hydro reservoir is set to 5% of the mean annual inflow. The fuel supply for biogas power plants is limited to a maximum of 5% of the annual electricity consumption, which is approximately the annual level of production of biogas from manure, agricultural residues and waste. Demand-response is one of the variation management options. Specifically, the aggregated consumers can curtail up to 5% of the demand at fixed costs within a given time period. More detailed description of the demand-response is provided in Table B1 in the supplementary material.

The assumptions made as to wind and solar photovoltaic (PV) densities (W/m^2) and available land are listed in Table 2. The available land is given as a share of the suitable land, which is equivalent to the total land excluding populated areas, natural parks, lakes, mountains, etc. The input data for VRE are obtained with the GIS model developed by Mattsson et al. [31]. To represent more accurately the capacity factors for wind and solar power, the wind and solar technologies are divided into five classes based on resource quality. The wind speed is translated into capacity factors based on the power curve for a typical wind farm equipped with Vestas 112 3.075 MW wind turbines. Solar irradiation is used to calculate the capacity factor profiles with the assumption that the PV technology is fixed-latitude-tilted. The data for calculating the capacity factors for wind and solar power generation are obtained from the Global Wind Atlas [37] and the ECMWF ERA5 database [38]. All the data for VRE profiles are based on the values for Year 2018.

Table 2
Assumptions made as to capacity limits for wind and solar photovoltaic. The density is the power output per unit area of a typical solar or wind farm.

	Solar Photovoltaic	Wind Onshore	Wind Offshore
Density [W/m^2]	45	5	8
Available land [%]	6%	10%	33%

The carbon cap is 10 g/kWh, which is roughly equivalent to a 98% reduction in CO_2 emission for the European electricity sector, as compared with the level of emission in Year 1990. The emission factor for natural gas is 198 gCO_2/kWh heat. The cost data and technical parameters for the main technologies are summarized in Table 3. These data are based on the cost projections for Year 2050 and are mainly taken from a previous report [39]. The initial investment cost is converted to the annualized cost with a discount rate of 5%.

To investigate further the breadth of conditions under which the choice of the demand pattern affects the modeling results, we conduct sensitivity analyses for the stylized case using different costs for wind, solar, transmission, and storage. Three levels of costs are assigned to each of the four technologies: “Low”, “Medium”, and “High”. The detailed cost assumptions are listed in Table B2 in the supplementary material. The reasons why the costs for wind, solar, transmission and storage are selected for the sensitivity analyses over all the other input parameters are: 1) these parameters are assumed to be the most important for the development of a VRE-based system; and 2) rather large uncertainties are attributed to these costs [44–47]. We also increase the carbon cap to 50 g/kWh to assess how the availability of flexible generation capacity affects the impact of the demand pattern on modeling results.

2.4. *The case of Europe*

The more detailed REX model [30], which is an energy system model used for policy support, is adopted to investigate the case of Europe. The countries included are the EU-28 (excluding Cyprus and Malta) plus Switzerland, Norway, Serbia, Bosnia and Herzegovina, North Macedonia, and Montenegro. These countries are divided into 13 regions and all the regions are assumed to be

Table 3
Cost data and technical parameters.

Technology	Investment cost [$/kW]	Variable O&M costs [$/MWh]	Fixed O&M costs [$/kW/yr]	Fuel costs [$/MWh fuel]	Lifetime [years]	Efficiency/Round-trip efficiency
Natural gas OCGT	493[a]	3.6	12.5	36[b]	30	0.35
Natural gas CCGT	800	3.6	10.5	36[b]	30	0.6
Biogas OCGT	493[a]	3.6	12.5	36[b]	30	0.35
Biogas CCGT	800	3.6	10.5	36[b]	30	0.6
Onshore wind	997	0	33	n/a	25	n/a
Offshore wind	2805[a]	0	93	n/a	25	n/a
Solar	674	0	8	n/a	25	n/a
Hydro reservoir	2464[a]	0	25	n/a	80	n/a
Hydro RoR	3696[a]	0	74	n/a	80	n/a
Transmission[c]	479 $/MWkm	0	9.6 $/MWkm	n/a	40	0.016 loss per 1000 km
Converter[c]	180	0	3.6	n/a	40	0.986
Battery[d]	156 $/kWh	0	0	n/a	10	0.9

[a] Schröder et al. [40].
[b] Eurostat [41].
[c] Hagspiel et al. [42].
[d] Cole et al. [43].

connected with HVDC grids, see Fig. 6. The synthetic electricity demand for Europe is created using the method of Mattsson et al. [31] for Year 2050. The demand profiles are treated in a manner similar to that used for the stylized case, so as to represent different seasonal and diurnal variations for the demand profile. The Scenarios for the case of Europe are presented in Table 4.

As for the input data for the case of Europe, the capacities of hydro reservoir and hydro RoR are kept constant at the current level due to environmental regulations in force. The capacity of hydropower is taken from the ENTSO-E statistics [34]. The inflow for each country is based on a previous study [15], and this value is divided into reservoir and RoR inflow based on the share of installed hydropower capacity. The assumptions made for the biogas power plants, wind, solar, transmission, storage, demand-response,

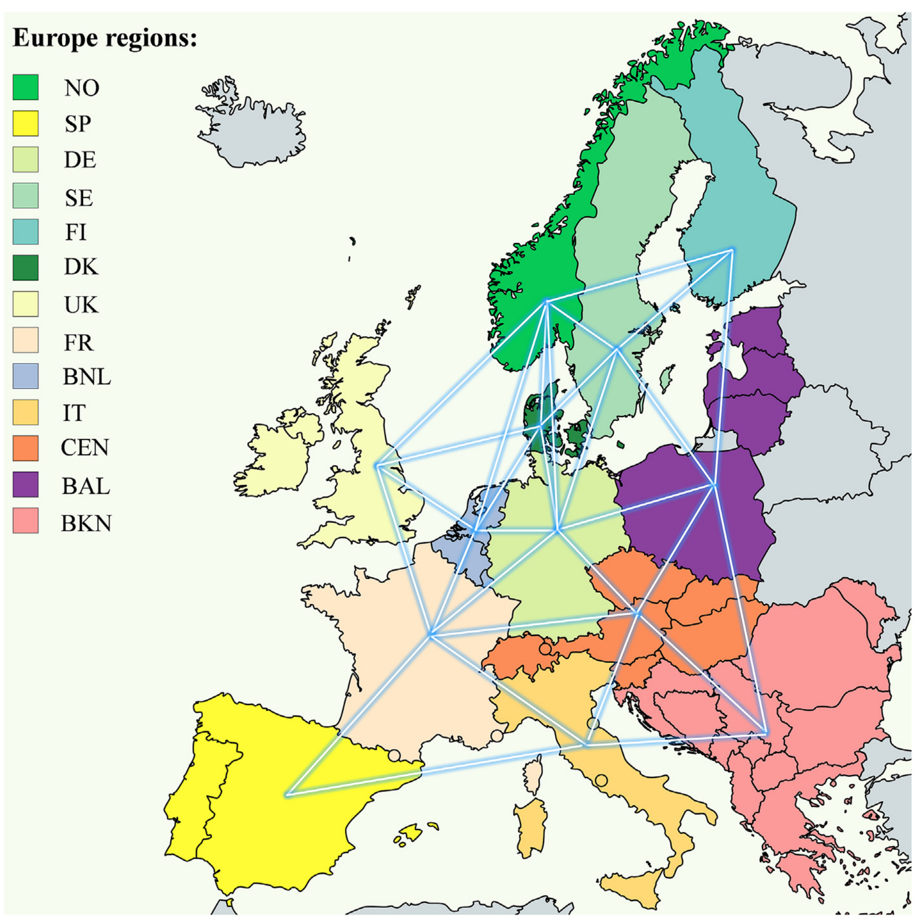

Fig. 6. Modeled regions and the interconnected transmission networks for Europe.

Table 4
Scenarios for the case of Europe.

Scenario[a]	Seasonal variation	Diurnal variation
Current demand pattern	Current pattern	Current pattern
Zero seasonal variation	Zero	Medium/High
Medium winter peak	15% of annual peak demand, winter peak	Medium/High
High winter peak	35% of annual peak demand, winter peak	Medium/High
Medium summer peak	18% of annual peak demand, summer peak	Medium/High
High summer peak	24% of annual peak demand, summer peak	Medium/High

[a] More detailed description of the scenarios for the case of Europe is presented in Table B3 in the supplementary material.

carbon cap, technology cost, and discount rate are the same as those in the stylized case. The model is then run for three weather years with different wind outputs for Europe. The main results are calculated based on the year 2005 when the wind output is at the average level [33]. 2008 and 2010 are selected for sensitivity analysis due to their higher (2008) and lower (2010) wind output [33]. By calculating the results for different weather years, we aim to investigate how the variation in output for wind, solar and hydropower on an interannual basis may affect the impacts of demand patterns on the modeling results.

To further evaluate whether the conclusions drawn from the stylized case hold for more detailed modeling analyses used for policy support, the electricity system cost and electricity supply mix for the case of Europe are compared with the results obtained from the stylized case. A summary of the method for this study is presented in Fig. 7.

3. Results

In this section, we present 1) the electricity system cost increases and the deviations in the electricity supply mix for the Scenarios of different seasonal variations compared with the Scenario of the *Current demand pattern*, and 2) the differences in electricity system cost and the deviations in the electricity supply mix for the Scenario of *High diurnal variation* compared with the Scenario of *Medium diurnal variation*. It is then possible to understand how different demand patterns affect the modeling results, particularly with respect to electricity system cost and the electricity supply mix. The mechanisms behind the impact of different demand patterns are further explained in Section 4.

3.1. Impacts of different seasonal variations for the stylized case

Fig. 8 shows how different seasonal variations of the demand profile affect the electricity system cost. Specifically, the figure illustrates how the average electricity system cost increases for Scenarios of different seasonal variations, as compared to the Scenario of the *Current demand pattern*. All the results are obtained under the conditions of medium diurnal variation, optimal transmission connection, and a carbon cap of 10 g/kWh. It is evident that if the annual peak of the electricity demand is in the winter (possibly due to large-scale deployment of electric heating), the system cost increase is low (<2% for all the Scenarios). Similarly, there is a low increase in the cost if the demand profile has no seasonal variation. In comparison, the system cost increases more if the annual peak is in the summer (possibly due to massive adoption of ACs). In such a case, the system cost increase is in the range of 3%–8%, depending on the amplitude of the summer peak.

The optimal generation and storage capacity mixes under the Scenarios of different seasonal variations are shown in Fig. 9. We choose one typical Scenario for each seasonal demand pattern to simplify the figure. The other members of the Scenario Group (see Table 1) display similar changes in capacity mix compared with the Scenario of the *Current demand pattern*. For Scenarios with zero seasonal variation and a winter peak, the electricity supply mix is similar to that for the current demand pattern. In contrast, scenarios with a summer peak display larger solar and storage capacity and are therefore quite distinct from the capacity mix that arises from using the current demand pattern.

A summary of the relationship between the difference in system cost and the deviations in the electricity supply mix for the Scenarios of different seasonal variations are shown in Fig. 10. The overall change in system cost is estimated as a maximum of 8%. In stark contrast, the deviation in the electricity supply mix is much

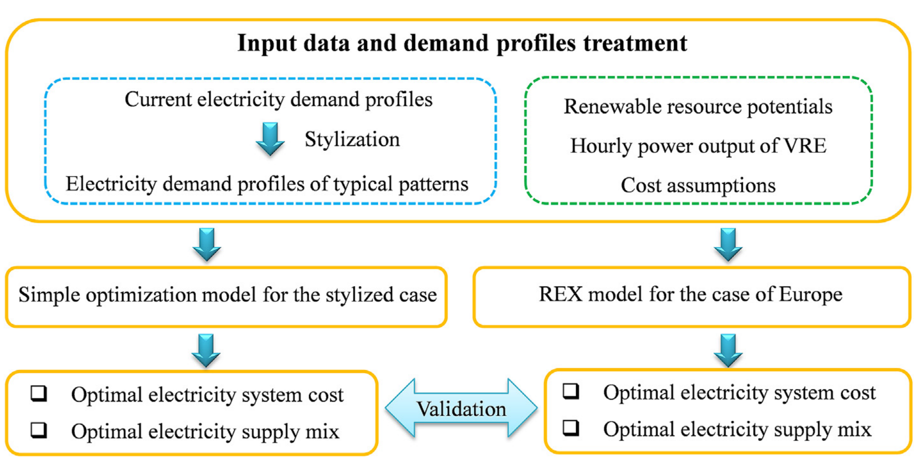

Fig. 7. Overview of the method. The input data for electricity demand and the stylization of demand profiles are shown in the blue dashed box. All the other input data are listed in the green dashed box. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

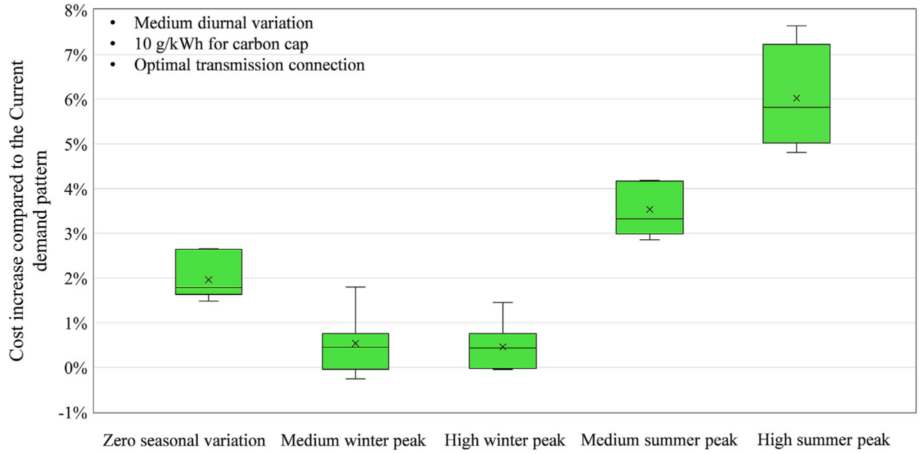

Fig. 8. Increases in the average electricity system cost for the Scenarios of different seasonal variations, as compared to the Scenario of the *Current demand pattern*. Each seasonal demand pattern (label on the *x*-axis) represents a Group of Scenarios with the same or similar aggregated demand profiles (for more details, see Table 1). The ends of the box are the upper and lower quartiles, so the box spans the interquartile range. The bar in the box represents the median value and the cross represents the average value. The whiskers are the two lines outside the box that extend to the highest and lowest values.

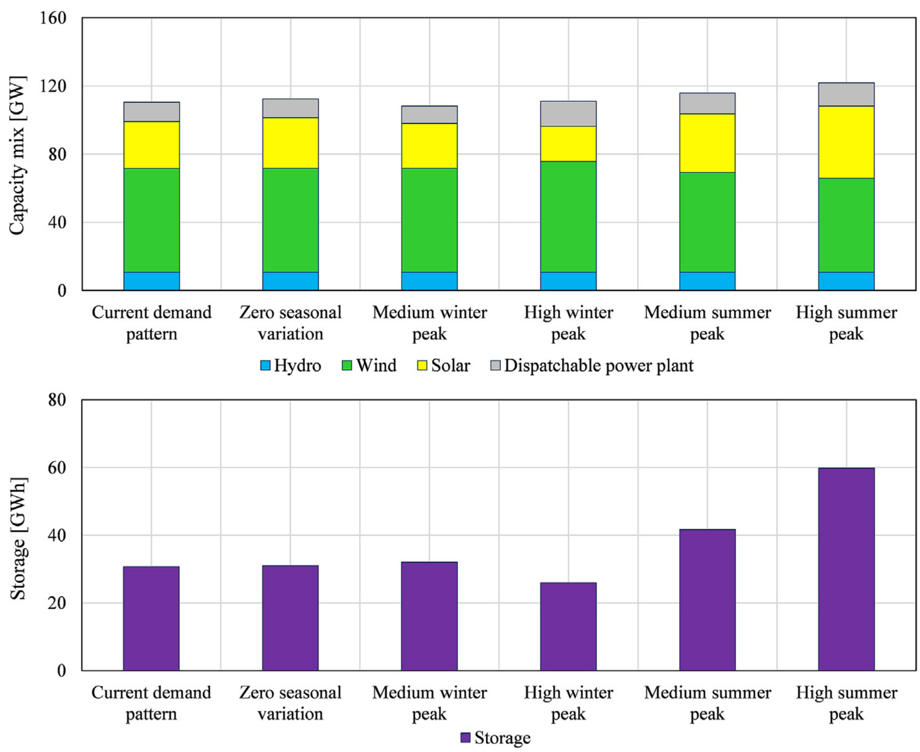

Fig. 9. Installed generation and storage capacities under the Scenarios of different seasonal variations. The capacity mix and storage for each seasonal demand pattern presented in this figure show the results of a sample scenario. All the members of each Scenario Group (see Table 1) have similar changes in capacity mix compared with the Scenario of the *Current demand pattern*.

larger. In the Scenario with the highest summer peak, the increase in system cost is 8%, while the investments in solar and storage capacities increase by 54% and 95%, respectively, as compared to the Scenario of the *Current demand pattern*. Similar phenomena are observed for other Scenarios. Therefore, it is clear that a change in seasonal demand pattern has a stronger impact on the electricity supply mix than on the system cost.

3.2. Impacts of different diurnal variations for the stylized case

The impacts of different diurnal variations (the cause of which may be various charging strategies for EVs) of the demand profile on the electricity system cost are depicted in Fig. 11. The figure shows the difference in electricity system cost for the Scenario of *High diurnal variation* compared to the Scenario of *Medium diurnal variation* under conditions of different seasonal demand patterns. Note first that a higher diurnal variation slightly increases the system cost regardless of the seasonal demand pattern. The impact of a higher diurnal variation is more evident for the demand profiles with a winter peak, while its influence is minor for the demand profiles with zero seasonal variation and a summer peak. In general, the difference in system cost between the Scenarios of

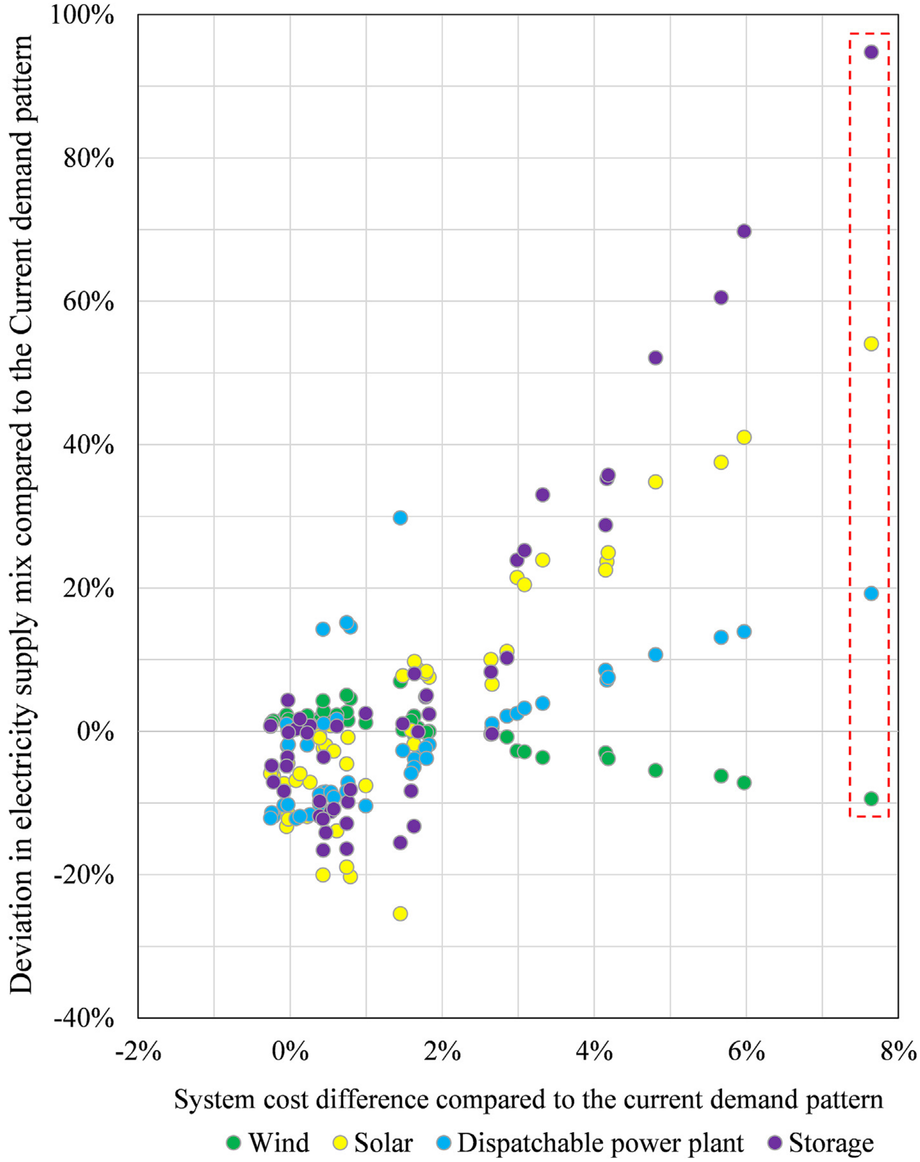

Fig. 10. The relationship between the difference in system cost and the deviations in the electricity supply mix for the Scenarios of different seasonal variations, as compared to the Scenario of the *Current demand pattern*. The dots inside the red rectangle represent the Scenario with the highest summer peak, as described in the text. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Medium- and *High diurnal variation* is limited (<3%).

Fig. 12 shows the relationship between the difference in system cost and the deviations in the electricity supply mix for the Scenario of *High diurnal variation* compared to the Scenario of *Medium diurnal variation*. Compared with the limited difference in the cost, there are substantial changes in the electricity supply mix, especially with regard to the capacities for solar and storage, in the Scenarios with a higher diurnal variation. In most cases, the system cost is higher for the Scenario with zero diurnal variation than for the Scenario with a diurnal variation (Fig. A1). This may seem counterintuitive, since the experience of a power system based on thermal power plants may have instilled in us the notion that any demand variation precipitates a need for peaking plants. As these plants have lower utilization times and higher running costs than base-load plants, they entail a higher system cost. Yet, here we show that it no longer holds for a renewable electricity system with a large share of VRE.

3.3. Impacts of flexible generation capacity for the stylized case

To further understand how the availability of flexible generation capacity affects the impact of the demand pattern on modeling results, we investigated a case with a higher carbon cap (50 g/kWh). A more generous carbon cap reduces the system cost increase due to a different seasonal variation for the electricity demand profile (Fig. A2). This is mainly because a less-stringent carbon cap allows for more generation capacity and more energy from dispatchable natural gas power plants. In such a case, the electricity system is better able to follow the change in the electricity demand profile, which means that a different demand pattern has a smaller impact on the electricity system and the corresponding system cost. A similar phenomenon would occur if we were to allow additional dispatchable generation technologies, such as fossil fuel plus CCS (carbon capture and storage) and nuclear power, in the modeling.

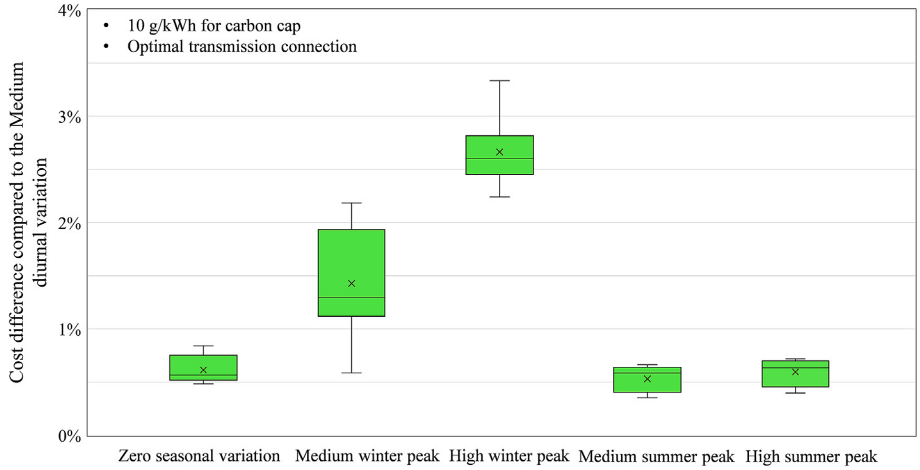

Fig. 11. Difference in the average electricity system cost for the Scenario of *High diurnal variation* compared to the Scenario of *Medium diurnal variation* under conditions of different seasonal demand patterns. Each seasonal demand pattern (label on the *x*-axis) represents a Group of Scenarios with the same or similar aggregated demand profiles (for more details, see Table 1). The ends of the box are the upper and lower quartiles, so the box spans the interquartile range. The bar in the box represents the median value and the cross represents the average value. The whiskers are the two lines outside the box that extend to the highest and lowest values.

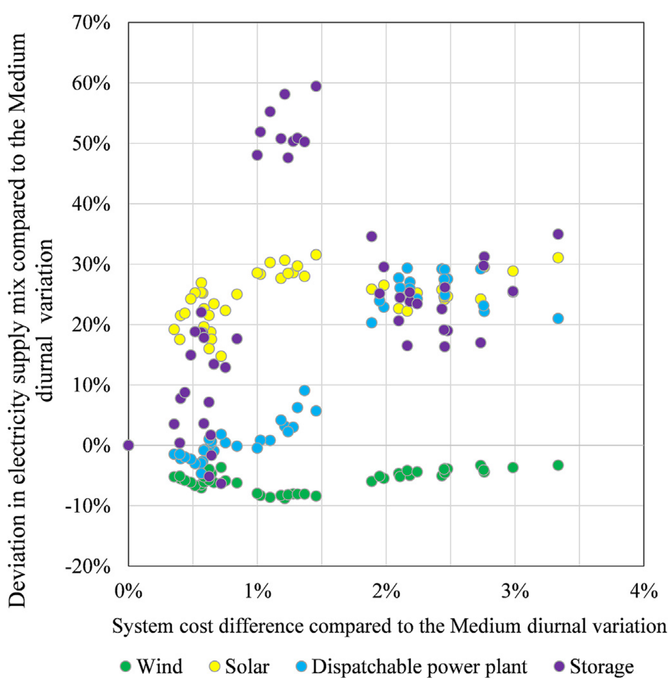

Fig. 12. The relationship between the difference in the system cost and the deviations in the electricity supply mix for the Scenario of *High diurnal variation* compared to the Scenario of *Medium diurnal variation*.

3.4. Sensitivity analysis

In the stylized case, the system cost increase is minor (<3%) for the Scenarios with zero seasonal variation and a winter peak, while the cost increases by up to 8% for a summer peak. We also conducted sensitivity analyses with different costs for wind, solar, transmission and storage, to see how the costs of the key technologies would affect the modeling results resulting from different demand patterns. The sensitivity analyses were conducted for one typical Scenario of the six different Scenario groups: *Current demand pattern*, *Zero seasonal variation*, *Medium winter peak*, *High winter peak*, *Medium summer peak*, and *High summer peak*. This choice ensures a wide coverage of cost differences resulting from different seasonal demand patterns and entails a reasonable overall computation time.

Fig. 13 shows how wind, solar, transmission and storage costs affect the differences in system cost between Scenarios with different seasonal variations and the Scenario of the *Current demand pattern*. Regardless of the cost parameters, the deviations in system cost due to different seasonal variations are consistent, with a greater increase in system cost for the summer peak than for the winter peak. Specifically, a low cost for solar power diminishes the system cost increase (to 5%) for the summer peak, and a high solar cost drives this value up to 9%. Similarly, a low cost for storage abates the system cost increase (to 3%) for the summer peak. A high cost for wind reduces the system cost increase for the summer peak, while the cost of transmission has little impact on the system cost.

3.5. Modeling results for the case of Europe

To understand whether the results from the stylized case hold for a full-scale model, we ran the REX model for Europe, to analyze how different demand patterns affect the modeling results for an energy system model used for policy support. As is shown in Fig. 14, there is a greater increase in system cost for the summer peak (up to 8%) than for the winter peak (<2%), as compared with the Scenario of the *Current demand pattern*. This result holds true when varying the weather years as input to the model, see Fig. A3 in the supplementary material. The variation in output for wind, solar and hydropower on an interannual basis has no significant influence on the impact of different seasonal demand patterns on system cost. The deviations in system cost due to different seasonal demand patterns for Europe as a whole are consistent with the results obtained for the stylized case, where the cost increase is less than 2% for the winter peak and up to 8% for the summer peak. Similar to the stylized case, a higher diurnal variation has only a minor impact on the system cost for Europe (Fig. A4) and the change in the demand pattern has a greater impact on the electricity supply mix than on the system cost (Figs. A5, A.6).

4. Discussion

Through investigating the impacts of different seasonal demand patterns on the system cost, we find that a summer peak can

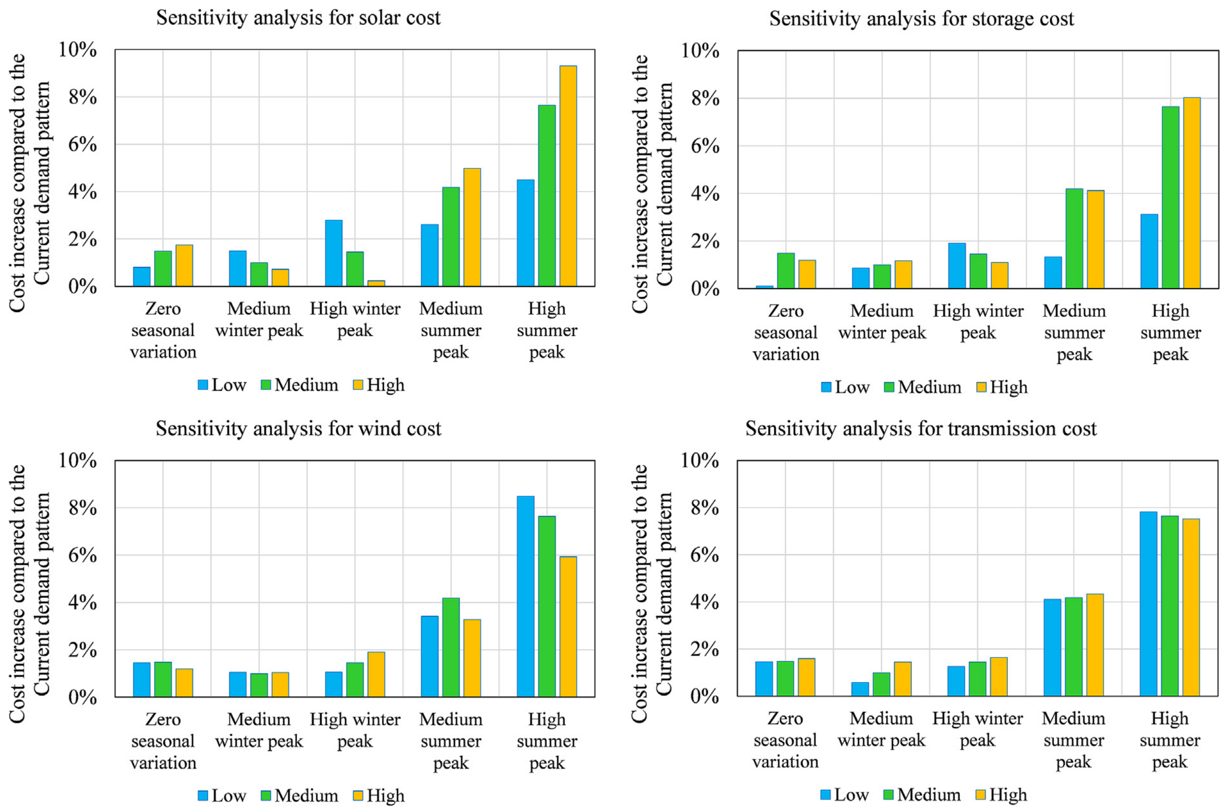

Fig. 13. Increases in the average electricity system cost for the Scenarios of different seasonal variations compared to the Scenario of the *Current demand pattern* under different cost assumptions for wind, solar, transmission and storage.

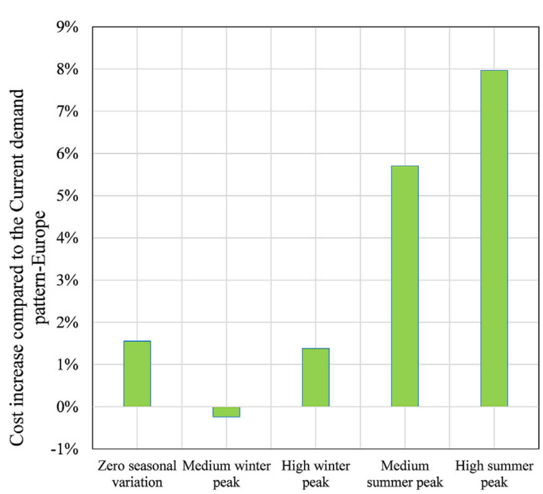

Fig. 14. Differences in the average electricity system cost between the Scenarios of different seasonal variations and the Scenario of the *Current demand pattern* for Europe. The input data for wind, solar and hydropower are based on the Year 2005.

increase the system cost by up to 8%, while the impacts of a winter peak and zero seasonal variation are limited (<3% increase in cost). This is because, in the stylized case, onshore wind power is cheap to install, and wind power has a typical seasonality with higher output in the wintertime than in the summertime. In addition, the variation of large-scale wind power can be smoothed through the expansion of transmission grids. Therefore, when the annual peak of the electricity demand is in winter, the seasonal variation of the demand profile is in line with the seasonal pattern of wind power, and cheap wind resource is deployed. In contrast, if the annual peak demand is in summer when the output of wind power is lower, the optimal system configuration contains more solar power and storage, which drives up the system cost. Correspondingly, there are large deviations in the capacity mix for the optimal electricity system portfolio, especially with respect to the solar and storage capacities. Overall, the deviations in the electricity supply mix are more evident than the changes in the system cost. The IEA report [48] analyzed the impact of increased cooling demand (a higher summer demand) on the electricity system and showed that a higher cooling demand increases the electricity cost as well as the total generation capacity. In the present study, both the electricity cost and the total generation capacity increase for the Scenarios with a summer peak as compared to the Scenario of the *Current demand pattern*, which is consistent with the conclusion of reference [48]. Similarly, Zhu et al. [49] assessed the effect of increased summer demand on the European electricity system, and estimated that a higher summer demand results in more installment of solar PV in South Europe, but the electricity cost remains stable. The results of Zhu et al. [49] are consistent with our findings regarding the impact of a higher summer peak on the electricity supply mix. The impact of a higher summer peak on electricity cost reported by Zhu et al. [49] is less influential than what we show, possibly due to the low amplitude of the summer peak in their electricity demand profile.

In reality, the electricity demand pattern is evolving over time due to climate change and increased sector coupling. The summer in Europe is becoming hotter, which will lead to the adoption of more ACs for cooling and, correspondingly, a higher demand in the summertime, as well as possibly a more pronounced daily peak. This is a possible case in which the demand pattern is genuinely influential. In such a case, if the modeler uses the historical electricity demand profile or linearly scales it up as the future electricity demand, misleading results might be produced, especially regarding the electricity capacity mix.

The impacts of different seasonal demand patterns on system cost are consistent, with a greater cost increase for a summer peak than for a winter peak, regardless of the cost assumptions for wind, solar, storage and transmission. As expected, a lower cost for solar and storage reduces the cost increase for the summer peak. This is because a lower cost for solar and storage avoids the system cost escalation that results from the large increases in solar and storage capacities. In addition, a more generous carbon cap or additional dispatchable generation capacity enables better load following for the system, which reduces the cost increase due to different seasonal demand patterns.

As for diurnal variation, the overall impact of different diurnal variations on the electricity system cost is limited (less than 3% increase in cost). Zappa et al. [24] analyzed investments in the European renewable electricity system under scenarios of different diurnal variations and found that a higher diurnal variation results in slightly more electricity generation, but the system cost is essentially unchanged. Similarly, Taljegard et al. [28] found that the optimal charging strategy for EVs has a minor impact on the system cost, as compared to direct charging based on the owners' driving patterns. The findings reported previously [24,28] are consistent with our results on the impacts of different diurnal demand patterns on the electricity system cost. In the present study, more dispatchable generation capacities are installed for Europe if the demand profile displays a higher diurnal variation, which is in line with the main findings in Ref. [25].

As for the case of Europe, the system cost increase for Scenarios with zero seasonal variation and a winter peak is <2% while the summer peak increases the system cost by up to 8%. The cost deviation due to different seasonal demand patterns for Europe is in line with the results from the stylized case. Therefore, our results regarding the impacts of different seasonal demand patterns based on the stylized case are valid for Europe. These results might not be universally true for regions with different resource endowments, see Appendix C for a contrasting example.

Note that we do not model with realism for the future European electricity system in this study, and the results should not be interpreted as indicative for either system design or operational strategy for the future electricity market. The exact numbers we present in this analysis are arguably of secondary interest. More relevant are the magnitude of error in modeling results if energy system modelers use historical demand profiles or linearly scale them up as input to the model. With this study we want to deliver a message to energy system modelers regarding whether or not potential future changes in the demand pattern should be considered for modeling practice. In most of the cases investigated for this study, the altered demand patterns have relatively weak impacts on system cost, yet greater influences on the electricity supply mix are observed. Thus, if the modeler is investigating details about the future electricity supply mix or the corresponding system operation, the future electricity demand pattern needs to be taken into consideration.

One limitation for this study is that we did not consider the volume change for the electricity demand, which can be a consequence of sector coupling. Following the integration with other sectors, such as heating, transportation and industry, both the volume of the electricity demand and the demand pattern will change. In such cases, due to dramatically increased electricity demand, the impacts of different demand patterns on the modeling results might be influenced by other factors, such as the land availability constraints for VRE. Therefore, we anticipate that future studies with a good representation of sector coupling will confirm or reject the universality of some of the conclusions drawn in this paper.

5. Conclusions and recommendations

In this paper, we use greenfield techno-economic cost optimization models to investigate the impacts of different demand patterns on modeling results for a stylized case with three interconnected regions in Europe and one full-scale applied case (Europe). Through analyzing the system cost and electricity supply mix, we show that:

1. In most cases (zero seasonal variation, winter peak), altered seasonal demand patterns have limited impacts on system cost (<3% increase in cost compared with the current demand pattern). In contrast, a summer peak may increase the system cost by up to 8%. With additional flexible generation capacities in the electricity system, the impacts of different seasonal demand patterns become negligible;
2. The impact on system cost of a greater diurnal variation is minor (<3% increase in cost);
3. The impacts of different demand patterns on a European highly renewable electricity system are in line with the results of the stylized case, with a system cost increase up to 8% for demand patterns that have a summer peak;
4. The electricity demand pattern has a stronger influence on the electricity supply mix than on the system cost, with differences of 0%−54% for solar power and 0%−95% for storage.

In Europe, the future electricity demand pattern is uncertain, but the potential changes in demand pattern are not consequential for the system cost (with the exception for demand patterns with a summer peak). In case the future electricity demand profile shifts from the current pattern to a summer peak, using historical demand profiles to represent future electricity demand in models may result in misleading results for the system cost. Yet, a future with a summer peak in demand is indeed possible, given that there would be massive adoption of ACs to deal with the hotter summers in Europe. Since we show that such a demand pattern may have a comparatively large (up to 8%) influence on system cost and an even larger impact (up to a factor of two) on capacity mix, it is important for modelers to exercise caution regarding the assumptions made for the future electricity demand pattern.

The conclusions that we draw in the present paper hold true for the European electricity system. They may not be valid for other regions due to, for example, different resource endowments. We anticipate future studies to test our hypotheses and to further evaluate the impact of different demand patterns on the modeling results for other regions.

Credit roles

Xiaoming Kan: Methodology, Formal analysis, Writing − original draft, Writing − review & editing. Lina Reichenberg: Conceptualization, Methodology, Writing − review & editing, Supervision. Fredrik Hedenus: Conceptualization, Methodology, Writing − review & editing, Supervision.

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. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2021.121329.

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