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ORIGINAL RESEARCH ARTICLE

Impacts of variation management on cost-optimal investments in wind power and solar photovoltaics

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This work investigates the impacts of variation management on the cost-optimal electricity system compositions in four regions with different pre-requisites for wind and solar generation. Five variation management strategies, involving electric boilers, batteries, hydrogen storage, low-cost biomass, and demand-side management, are integrated into a regional investment model that is designed to account for variability. The variation management strategies are considered one at a time as well as combined in four different system contexts. By investigating how the variation management strategies interact with each other as well as with different electricity generation technologies in a large number of cases, this work support policy-makers in identifying variation management portfolios relevant to their context. It is found that electric boilers, demand-side management and hydrogen storage increase the cost-optimal variable renewable electricity (VRE) investments if the VRE share is sufficiently large to reduce its marginal system value. However, low-cost biomass and hydrogen storage, are found to increase cost-optimal investments in wind power in systems with a low initial wind power share. In systems with low solar PV share, variation management reduce the cost-optimal solar PV investments. In two of the regions investigated, a combination of variation management strategies results in a stronger increase in VRE capacity than the sum of the single variation management efforts.

Introduction

To mitigate climate change, transformation of electricity systems worldwide is required. Wind and solar power offer electricity that is associated with no or low emissions of greenhouse gases and, with the cost developments seen over the past decade, they do so at a competitive cost. However, the value factors of wind and solar (i.e. the average wind/solar PV owner revenue relative the average annual marginal cost of electricity) are reduced as their penetration levels increase [1]. This reduction can be mitigated by variation management strategies (VMSs), which can facilitate load following, provide reliable complements and decrease curtailment [2]. In describing the functions of the individual VMS in the electricity system, this work uses the categories of VMSs proposed by Göransson and Johansson [2]: (i) absorbing technologies, which exploit excess generation; (ii) complementing strategies, which include peak-load and mid-load electricity generation technologies, as well as reservoir hydropower, which can produce electricity during hours of low levels of wind and solar generation; and (iii) shifting technologies, which are used for shifting in time either the demand or generation. The present work covers VMSs that pertain to all three categories, employing electric boilers and hydrogen storage as absorbing strategies, low-cost biomass as a complementing strategy and demand-side management (DSM), flow batteries and lithium-ion batteries as shifting strategies. A thorough review of different strategies for variation management is given by Lund et al. [3].

Absorbing strategies, such as power-to-gas and power-to-heat, connect the electricity system to other energy-intensive sectors. Recently, Hou et al. [4] have investigated the system impact of hydrogen storage and found that it can increase the value of wind power and they conclude that hydrogen storage is of greater value

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to the system if the hydrogen is sold to hydrogen consumers rather than being converted back to electricity using fuel cells. Complementing strategies have also been investigated. Hirth [5] have assessed hydropower as a flexible complement to variable renewable energy sources (VRE) and shown that it increases the value factor of wind power. The importance of peak-load and mid-load technologies for VRE integration has been highlighted by Hirth [1]. Increasing the flexibility of historically inflexible electricity generation has been examined by Garðarsdóttir et al. [6], who have shown that improving the flexibility of coal-based technologies improves the conditions for wind and solar power investments in regions with moderate conditions for wind and solar power generation. The main shifting strategies, which include different battery storage technologies and DSM, have been shown to benefit solar photovoltaic (PV) generation [7], while exerting a weak impact on the value factor of wind power [2].

Previous studies of variation management have often been limited to one or a few VMSs, and few of these studies have included investments in VMSs in the optimisation process. Mathiesen and Lund [8] performed an analysis in which they included seven different variation management technologies exogenously. They found that coupling a high wind system with heating generation resulted in substantial fuel savings. They also found that the cost of integrating VRE at high levels of wind penetration was reduced when electrolysers were used. Kiviluoma and Meibom [9] have shown that wind power benefits more from flexibility provided by electric boilers with heat storage than from flexibility provided by electric vehicles. Their model included in the optimisation process both investments in electric boilers and heat storage capacity, whereas electric vehicles were implemented exogenously. Several VMSs were included in a recent study conducted by Kiviluoma et al. [10]. The strategies were included one-by-one and all together in a model that soft-linked generation planning and operation planning. They reported transmission grid expansion and increased electrification of district heating as the strategies that created the highest system savings. They also highlighted that there were significant differences in the results from the investment model and the operation model, and they concluded that improvements are needed to obtain more accurate investments in VMSs.

The aim of the present work is to investigate how different variation management technologies, applied separately or in combination, affect the cost-optimal system composition, by co-optimizing the investment and dispatch of the electricity system. The roles of the different VMSs and how they interact with each other as well as with different types of electricity generation technologies is in focus. The work is carried out to provide policy makers with information on competition and synergies between possibly attractive tools for managing the variations in future electricity systems with different conditions for wind, solar and hydropower.

Methodology and input data

This section presents the model, together with the details of the implementation of the different variation management strategies. The data applied to represent the generation technologies are presented in the *Data* sub-section. The section ends with a basic description of the terms ''system-limited'' and ''resource-limited'', which are subsequently used to describe different system conditions for wind and solar generation.

Model

The regional investment model applied in this work (see Appendix C) was first presented by Göransson et al. [11]. This is a linear model that minimises the costs of investments and operation to meet the demand for electricity. The model accounts for variability by including start-up costs, start-up time, and minimum load level of thermal generation, employing an hourly temporal resolution. The model is run for 1 year, representing Year 2050 in terms of restrictions on greenhouse gas emissions (no net emissions are allowed), cost reductions from exogenous learning for wind and solar power (the assumed investment costs are listed in Table B1 in Appendix B), and efficiency improvements for thermal generation (the assumed efficiencies are included in the running costs in Table B1 in Appendix B). Four regions, ES3, HU, IE, and SE2 (for the map see Figure B2 in Appendix B), with load data and conditions for wind and solar power generation from central Spain, Hungary, Ireland, and southern Sweden (price area, Stockholm), are modelled separately and trade in electricity is not included in the model. A green-field approach is taken, so the existing electricity generation capacity in the regions is not considered. Electrification of parts of the industrial sector is assumed by Year 2050, increasing the annual electricity demand by 20% compared to today's levels, as given by ENTSO-E [12]. This new industrial demand is assumed to be in the form of hydrogen production, and it is evenly distributed over the year.

In this work, the model has been complemented with five different VMSs: electric boilers; batteries; hydrogen storage; low-cost biomass; and DSM. Electric boilers are here considered to be an opportunistic absorbing strategy of low-cost electricity. The impact of electric boilers is evaluated in the two regions in which district heating systems are present (Hungary and southern Sweden) as shown in Table 1 [13]. Two types of batteries, lithium-ion batteries and flow batteries are included in the battery cases. As explained at the beginning of this section, this work assumes an industrial hydrogen demand that is supplied through electrolysis, which requires a certain level of investment in electrolyser capacity in all the cases. However, with an over-investment in electrolyser capacity and investments in hydrogen storage, the production of hydrogen can be distributed in time and thereby provide variation management in the form of a shifting strategy. Hydrogen with storage is however likely to act more as a combination of an absorbing and complementing strategy due to the low costs of storing hydrogen on a large scale. Biomass-based generation can assume the role of a complementing strategy in a CO_2-neutral electricity system, in the *Low-cost biomass cases*, biomass is available at a lower cost compared

TABLE 1

The analysed cases for each region.

	ES3	HU	IE	SE2
No Flex[a]	x	x	x	x
Electric boilers		x		x
Batteries	x	x	x	x
H_2 storage	x	x	x	x
Low-cost biomass	x	x	x	x
DSM	x	x	x	x
Full Flex[b]	x	x	x	x

[a] No Flex – incudes none of the VMSs.
[b] Full Flex – incudes all the VMSs.

to the other cases. DSM is implemented as the possibility to shift a given share of the load for up to a given length of time, as proposed by Göransson et al. [14], with complementary information from Zerrahn and Schill [15]. Appendix A is dedicated to the implementation of these five VMSs, whereas the input data are presented in the next sub-section. The cases included for each region are presented in Table 1.

Data

Economic data for the electricity generation technologies is based on data from IEA World Energy Outlook 2016 [16], with complements for wind power [17] and thermal cycling [18,19]. Biogas is assumed to be produced through the gasification of solid biomass, biogas is thereby connected to the biomass prices [20]. The wind power production is modelled as modern wind farms with historical re-analysis data [21–25]. Solar PV is modelled as mono-crystalline silicon cells installed with optimal tilt with one generation profile for each region [26]. Hydropower is modelled for the region southern Sweden representing the local hydropower and the hydropower imported from northern Sweden, with historical limits on ramp-rates [27,28,2]. Economical and technical data for variation management technologies was acquired from the Danish energy agency, Energistyrelsen [29]. The heat price is a simplification based on the modelled price for district heating in Gothenburg [30,31]. Tables on the technical and economic data as well as further description of the data are found in Appendix B.

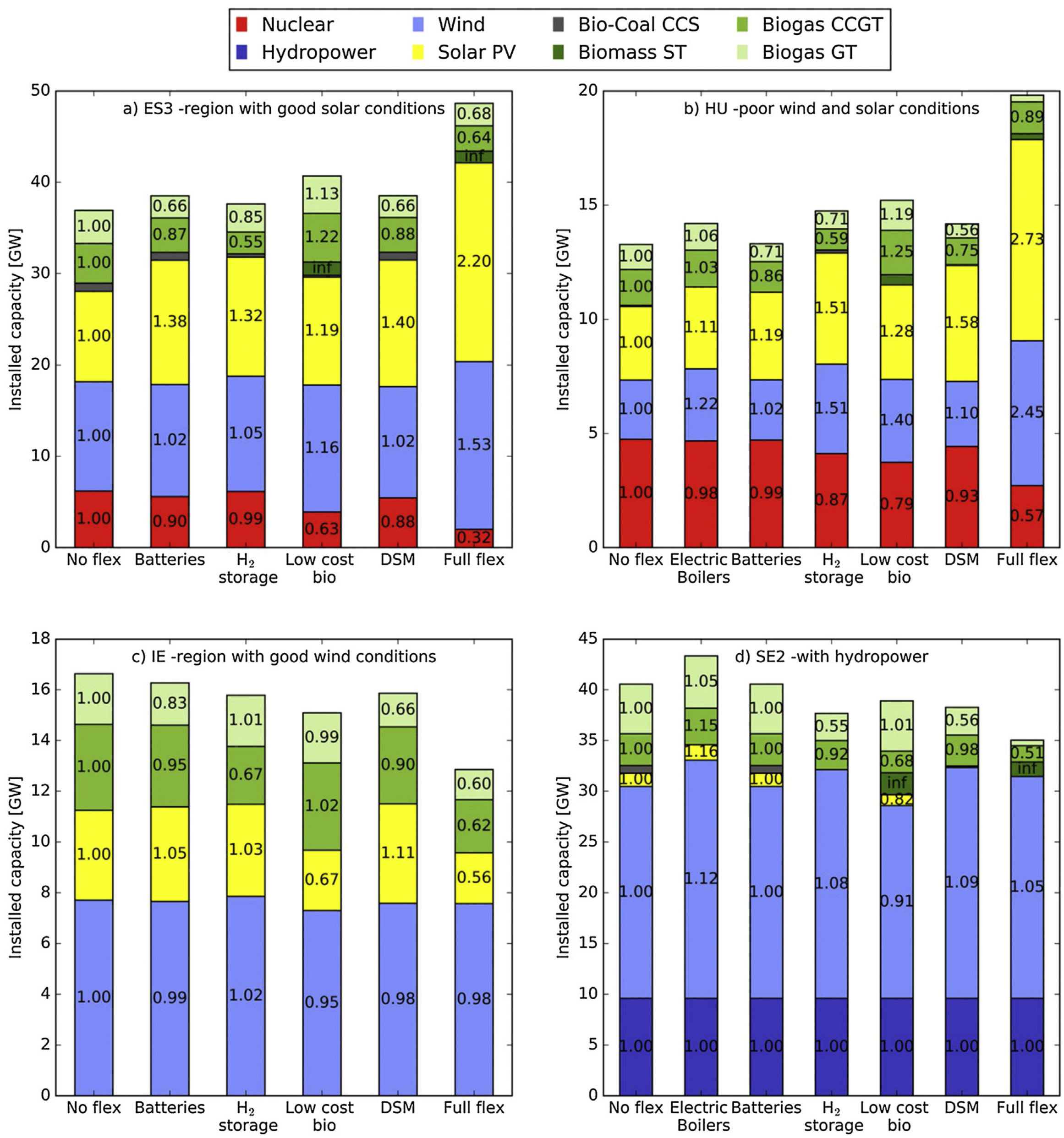

FIGURE 1

Installed capacities in each VMS scenario in the four regions. The number in each box represents the share of capacity compared to the No Flex case; thus, capacities that are not present in the No Flex case are denoted as ``inf" (infinitely). The values for capacities of less than 1 GW are removed to improve readability. The Full Flex case combines all the other VMSs.

System-limited and resource-limited capacities

In this work, we investigate the impacts of VMSs on the cost-optimal investment levels of the generation technologies in the system. For wind and solar power, the cost-optimal investment level depends not only on the relationship between the investment and running costs relative to other technology options (what traditionally has been given from screening curves), but also on the cost-competitiveness of complements, the value of electricity during the hours of generation, and the extent of the curtailment. In the present work, we use the concept of ''system-limited'' wind or solar capacity to refer to a situation where the cost-competitiveness and marginal system value of the VRE technology analysed are substantially reduced due to high levels of the same technology being present in the system, thereby inhibiting further investments. However, if the conditions for wind or solar generation are poor at the available sites, the VRE technology is outcompeted already before the investments are sufficiently large to affect the marginal system value. In such a situation, we refer to the VRE capacity as being ''resource limited''.

Results

Figure 1 gives the cost-optimal system composition with and without variation management for the four regions considered. As illustrated by Figure 1, there is a substantial difference in system composition between the regions already without variation management in place (the *No Flex case* in Figure 1) as a result of differences in demand profile and conditions for wind, solar and hydropower. The regions without good conditions for wind power (central Spain and Hungary), have base-load generation in the form of nuclear power capacity (Figure 2a–b) in the cost-optimal capacity mix whereas the regions Ireland and southern Sweden are supplied by electricity from renewable sources only (Figure 2c–d). In the systems investigated that have nuclear power in the capacity mix the VMSs increase the total installed capacity relative the cases without variation management (Figure 2a–b), as VRE mainly replace nuclear power capacity which has more full-load hours. In systems that lack base-load generation (Ireland and southern Sweden) the VMSs instead typically reduce the total installed capacity (Figure 2c–d) by reducing curtailment and investments in biogas turbine capacity.

When comparing the impact of VMSs on the capacity mix of the different regions, a number of general trends emerge. Shifting strategies, such as DSM and batteries, tend to be particularly efficient at increasing the cost-optimal solar PV investments while reducing investments in gas turbine capacity, whereas the ability to invest in hydrogen storage efficiently increases the cost-optimal wind power investments in most regions. However, there are exceptions to these rules of thumb. For example, in central Spain, which has highly favourable conditions for solar PV generation, all the VMSs increase substantially the cost-optimal solar investments, albeit with a lower impact on wind power investments in general. Similarly, in southern Sweden, which has poor solar conditions but good wind conditions, the VMSs displace solar PV investments. To understand these trends, we return to the concept of system-limited and resource-limited capacities. From the results, it is clear that absorbing and shifting VMSs mainly support system-limited VRE whereas resource-limited VRE derive little or no benefit from these strategies (wind power in central Spain and solar PV in southern Sweden). This is logical, since shifting and absorbing strategies increase the value of VRE by shifting generation in time or by absorbing excess generation. For resource-limited solar PV, VMSs can even reduce the value of solar generation, as variation management strategies typically reduce the cost of meeting the electricity demand at the mid-day peak (southern Sweden in Figure 1d).

In the case of resource-limited wind power, low-cost biomass can act as a support. Since low-cost biomass is a complementing strategy and wind power that is paired with a complement can replace base-load generation, a reduction in the cost of the complement increases the cost-competitiveness of the pair. Low-cost biomass is for example the only variation management strategy that increases substantially the resource-limited wind power investments in central Spain (Figure 1b). However, in the absence of base-load generation, as in southern Sweden and Ireland, low-cost biomass reduces the cost-optimal investments in VRE (Figure 1c–d).

The *Full Flex case* include all of the VMSs and thereby includes the highest amount of options for flexibility. In this case the peak-load investments are reduced in all four regions, as are the base-load investments in the two regions where they exist. The total impact of all VMSs on investments in VRE capacity vary greatly between regions, and a low impact is observed for regions with system-limited wind power (which have high VRE share already without VMSs) whereas the VRE capacity doubles or even triples in

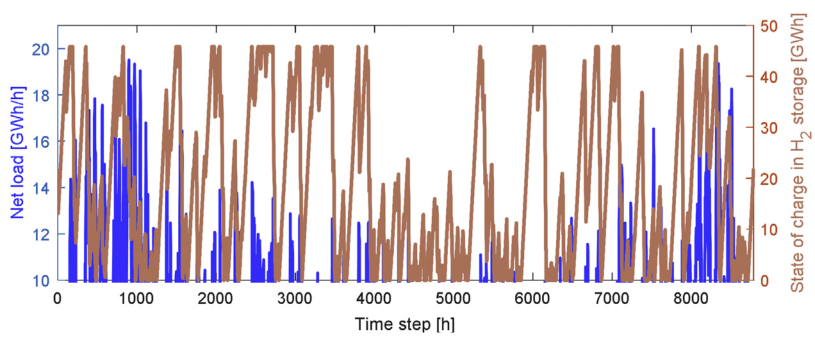

FIGURE 2

The operation of the hydrogen storage in region SE2 and the net load above 10 GW in the same region for the year investigated. (In region SE2 there is hydropower capacity of 9.6 GW given exogenously.) The hydrogen storage is subject to around 20 large cycles over the year. Charging is slow, typically around a week, whereas discharging is faster, typically around one to two days, and highly correlated with net load events above 10 GWh/h.

TABLE 2

Levels of storage, electrolyser capacity, total cost, curtailment, shares of different generation types, and biomass usage for the different cases in the ES3 region.

ES3 – central Spain	No Flex	Batteries	H_2 storage	Low-cost biomass	DSM	Full Flex
Flow Battery [GWh]	0.0	12.0	0.0	0.0	0.0	2.9
Electrolyser [GW]	3.0	3.0	5.1	3.0	3.0	5.2
H_2 storage [GWh]	0.0	0.0	159	0.0	0.0	121
Total Cost [M€/yr]	7,910	7,790	7,450	7,650	7,430	6,900
Curtailment [TWh/yr]	4.2	3.4	3.6	4.8	4.1	6.8
VRE share	0.44	0.51	0.51	0.51	0.51	0.75
Complements share	0.12	0.10	0.04	0.21	0.10	0.11
Base share	0.44	0.39	0.45	0.29	0.39	0.14
Biomass use [TWh/yr]	18.1	15.3	6.3	43.9	15.3	25.7

HU – Hungary	No Flex	Electric boilers	Batteries	H_2 storage	Low-cost biomass	DSM	Full Flex
Flow Battery [GWh]	0.0	0.0	2.5	0.0	0.0	0.0	0.0
Electrolyser [GW]	1.5	1.5	1.5	2.1	1.5	1.5	2.2
Electric boilers [GW]	0.0	1.8	0.0	0.0	0.0	0.0	1.9
H_2 storage [GWh]	0.0	0.0	0.0	40.8	0.0	0.0	57.4
Total Cost [M€/yr]	3,980	3,960	3,950	3,810	3,890	3,790	3,610
Curtailment [TWh/yr]	0.4	0.3	0.2	0.6	0.6	0.4	1.0
VRE share	0.22	0.25	0.24	0.33	0.30	0.29	0.52
Complements share	0.06	0.05	0.05	0.04	0.13	0.05	0.07
Base share	0.72	0.70	0.71	0.63	0.57	0.67	0.41
Biomass use [TWh/yr]	6.2	6.1	5.3	3.3	14.3	4.8	7.9

IE – Ireland	No Flex	Batteries	H_2 storage	Low-cost biomass	DSM	Full flex
Flow Battery [GWh]	0.0	2.0	0.0	0.0	0.0	0.0
Electrolyser [GW]	1.1	1.1	1.8	1.1	1.1	1.6
H_2 storage [GWh]	0.0	0.0	80.5	0.0	0.0	54.4
Total Cost [M€/yr]	2,350	2,340	2,150	2,200	2,230	1,960
Curtailment [TWh/yr]	6.8	6.5	5.6	5.5	6.2	4.3
VRE share	0.82	0.83	0.90	0.80	0.84	0.87
Complements share	0.18	0.17	0.10	0.20	0.16	0.13
Biomass use [TWh/yr]	14.2	13.6	8.5	16.4	12.8	10.6

SE2 – southern Sweden	No Flex	Electric boilers	Batteries	H_2 storage	Low-cost biomass	DSM	Full Flex
Electrolyser [GW]	3.40	3.4	3.4	3.9	3.4	3.4	3.7
Electric boilers [GW]	0.0	4.4	0.0	0.0	0.0	0.0	2.9
H_2 storage [GWh]	0.0	0.0	0.0	45.9	0.0	0.0	102
Total Cost [M€/yr]	6,940	6,890	6,940	6,760	6,670	6,670	6,350
Curtailment [TWh/yr]	5.7	8.2	5.7	7.6	2.9	7.5	3.8
VRE share	0.62	0.65	0.62	0.64	0.57	0.65	0.62
Complements share	0.38	0.35	0.38	0.36	0.43	0.35	0.38
Biomass use [TWh/yr]	17.0	18.0	17.0	17.5	34.0	16.2	21.5

the regions with resource-limited wind power and system-limited solar PV. In southern Sweden, the low biomass price in the *Full Flex case* promotes the use of biomass steam power plants and the share of the demand supplied by VRE is at the same level as the *No Flex case*. In Ireland, with very good wind conditions and system-limited wind power, the VMSs reduce investments in wind and solar while increasing the share of the annual electricity demand supplied by VRE, given in Table 2. In central Spain and Hungary, which have resource-limited wind power, a combination of VMSs increases the value of wind power much more than the sum of the single strategies. In both central Spain and Hungary, the shifting and absorbing strategies increase the cost-competitiveness of solar power, which in turn reduces the cost-competitiveness of the base-load technologies, while complementing strategies boost the cost-competitiveness of resource limited wind power, resulting in a massive increase in VRE share at the expense of base-load generation.

The need for complements increases with increasing VRE share in regions with base-load generation. The combination of all VMSs in the *Full Flex case* holds back a large part of the increase in biomass usage experienced in the *Low-cost biomass case* and the share of the electricity demand that is supplied by complementing technologies (i.e. biomass steam, combined cycle biogas turbines and biogas turbines) in the *Full Flex case* is almost equivalent to the share in the *No Flex case* in central Spain, Hungary and southern Sweden (see Table 2), whereas the share of the demand supplied by base-load generation (i.e. nuclear power) is substantially lower in the *Full Flex cases* compared to the *No Flex cases*.

In the *H_2 Storage case*, the dimensioning of the hydrogen storage and electrolyser is made based on the same rationale in all regions investigated. Figure 2 gives the operation of the hydrogen storage in southern Sweden. Due to the high cost of the electrolyser relative the hydrogen storage, the hydrogen storage is charged during all non-peak hours and thus the size of the electrolyser is mainly dictated by the time between peak-load events and the hourly hydrogen demand. For the regions investigated, the electrolyser is required to operate at rated power for between 4.5 days (Hungary) to 6.7 days (central Spain) to fully charge the hydrogen storage. The size of the storage determines the discharge time. Thus, the dimension of the storage is strongly influenced by the duration of the peak-load events and the hourly hydrogen demand. For the regions investigated, a full storage can supply the hydrogen demand for between 1.8 days to 5.4 days, with lowest storage persistence in Hungary with the lowest wind share and the highest storage persistence in Ireland with the highest wind share. With hydrogen storage, the hydrogen demand does not require any dedicated investments in load-following technologies. Instead, it increases the value of wind and solar power, by storing electricity from low-net-load events to supply hydrogen during net-load peaks. This increased value of VRE increases its competitiveness relative base load generation. In the *Full Flex case*, investments in hydrogen storage and electrolyser capacity are lower in central Spain and Ireland due to the presence of DSM and batteries, which co-operate with the hydrogen storage to reduce the peak-load events. In Hungary, the hydrogen storage and electrolyser capacity are increased to accommodate more wind power and in southern Sweden the electrolyser capacity is reduced while the hydrogen storage capacity is increased such that it takes 20 days to fill the storage. This to match the combination of VMSs and hydropower in southern Sweden which result in long time periods between peak net-load events.

Electric boilers offer an additional off-set for electricity on the heat market, which increases the value of wind power but also stimulates investments in biogas technologies. In Hungary, the electric boiler capacity is dimensioned to fulfil the spring and autumn demands for heat in the *Electric boiler case*. In the *Full Flex case,* the electric boiler capacity in Hungary is higher due to the extensive VRE capacity. In southern Sweden, the electric boilers see a maximised investment in the case where they are the sole VMS, whereas the investment is somewhat reduced it the *Full Flex case*. The reduction in the electric boiler capacity happens despite a very low investment cost and is attributed to the fact that most of the remaining curtailment happens during the summer months.

In the *Battery cases*, there are investments in flow batteries in three of the regions. Central Spain sees the largest investment in batteries, mainly due to the large share of solar PV generation. However, in the *Full Flex case* with other VMSs being available, this investment is reduced from 12 GW h to 3 GW h, regardless of the increased solar PV capacity. The battery capacities in Hungary and Ireland are eliminated in the *Full Flex case*. Thus, batteries compete with the other variation management options available in the *Full Flex case*. DSM, which is available at no cost in the *Full Flex case*, reduces the marginal cost difference over a 12-h time-frame, thereby severely reducing the inducement to invest in batteries. In Southern Sweden, batteries are not invested in even if other variation management strategies are excluded (i.e. in the *Battery case*).

Variation management strategies reduce total system costs and the VRE share is increased in most of the cases, as shown in Figure 3. In southern Sweden, which has a large fraction of inbuilt flexibility from hydropower already in the *No Flex case*, the system savings from variation management strategies in the *Full Flex case* is about 8%. The cost savings are as high as 17% in Ireland, due to the reduced need for investments in generation capacities. The cost savings are mostly derived from hydrogen storage, DSM and the usage of low-cost biomass, of which the two latter VMSs are of no cost. The use of batteries generates fairly large cost savings in central Spain, but only minor savings in the other regions. The electric boilers have a weak impact on the total cost, although they increase the share of VRE in the two systems where they are examined.

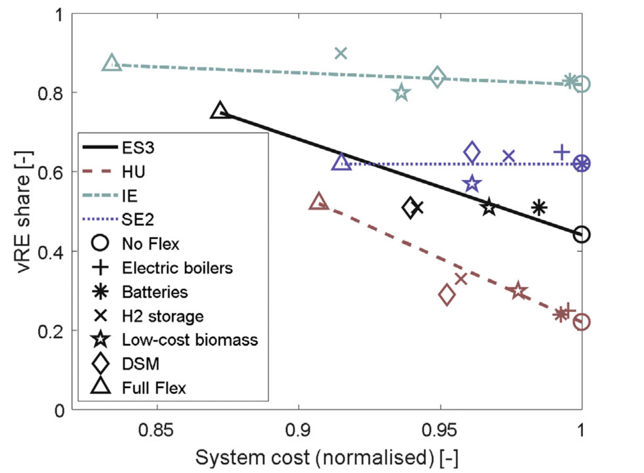

FIGURE 3

The VRE share and the system costs (normalised to the cost in No Flex case) for the different cases. The lines are drawn between the No Flex and the Full flex cases.

Discussion

The findings of this work change the perspective on variation management strategies in three important ways:

1) Variation management is often considered as strategies to mainly reduce the need for investments in peak-load capacity. The present study shows that variation management influences the cost-optimal level of investments for all types of generation, and while some strategies, such as DSM, are very efficient at reducing the need for peak generation, other strategies, such as electric boilers boost the investments in VRE without reducing investments in peak capacity.
2) Variation management strategies are expected to compete with each other. The present work shows that there are VMSs that complement one another and that a combination of VMSs may even have an impact that is greater than the sum of the individual impacts (see Figure 2a and b).
3) Variation management strategies are expected to promote base-load generation. This is a common observation when analysing the impact of variation management on the operation of an electricity system, where the inclusion of VMSs typically increases the number of full-load hours for base-load generation. In this work, where the impact of VMSs on the cost-optimal system composition is considered, it is found that variation management boosts VRE investments and displaces base-load investments. Indeed, base-load investments are reduced consistently in the VMS cases (see Figure 2a and b).

Furthermore, the present work illustrates that the nature of the energy storage can lead to significantly different impacts. In the case of lithium-ion batteries, the costs are proportional to the storage volume, and the charge and discharge capacity is typically large relative to the storage volume (i.e., C-factors in the range of 0.5–1.0 are common). These characteristics make batteries a good fit for frequent variations of high amplitude, such as solar power variations. However, the properties of hydrogen storage, entailing expensive electrolyser investments for charging but significantly lower storage costs, make this solution a better fit for variations of lower amplitude and frequency, such as variations in wind power generation. However, with the costs for hydrogen storage and the electrolyser being assumed here, this VMS is dimensioned to reduce investments in thermal generation rather than to absorb curtailed wind power generation, which would require a larger electrolyser and more storage to enable longer discharge times. Nevertheless, the hydrogen storage increases substantially the value of wind power and stimulates wind power investments in all the regions.

The demand for electricity for hydrogen production is in this model a fixed base load that is added to the normal electricity demand, corresponding to 20% of the total annual electricity demand. This base-load without storage makes the system less variable (the relative difference between the day-time and night-time loads is reduced) and may promote investments in traditional base-load generation.

In this work, DSM is added exogenously without accounting for the costs associate with its implementation and administration. In addition, DSM is implemented on a large-scale throughout the year, whereas it may represent mainly the electricity demands for heating and cooling, which are focused on parts of the year. This approach to DSM may down-play the role of batteries, which compete to provide the same variation management service in the *Full Flex cases*.

This paper aims to capture how investment decisions depends on the intra-year variability from hours to the full year but excludes variations within the hour and between years as well as not trying to capture a pathway from today's system. Hourly, diurnal and weekly variations are well represented by accounting for a full year in the optimization and by considering four regions with different wind and solar generation profiles in the analysis. Inter-yearly differences can move the equilibrium between VRE and base-load as well as the need for peak capacity. To study these investment dynamics even further it could be of interest to look at weather patterns for several years. It is therefore important to highlight that the results from this work should not be used for real investment decisions, but for understanding the dynamics between different variation management strategies under different wind and solar resource conditions.

All usage of variation management strategies is scheduled perfectly, since all generation is known from the perfect foresight and controlled to minimise the societal costs. Thus, the benefit of the variation management strategies on hourly scheduling may be overestimated, while the ability of variation management to support the system to tackle uncertainty is disregarded. In addition, uncertainties in VRE generation which for the industrial sector may be solved by procurement strategies such as described in Nojavan & Aalami [32], are not included in this work.

The cost savings derived from electric boilers are small in this work, albeit not insignificant. The generation capacities, mainly of VRE, increase in both Hungary and southern Sweden in the *Electric boiler case*. This work could be followed up by work considering a representation of the heat sector including hourly heat demand, other options to provide heat as well as heat storages.

Finally, this work considers variation management in regions in isolation. Variability can also be reduced by trade. The interplay between trade and the variation management strategies investigated here would be another valuable addition to this work.

Conclusion

This work investigates the impact of a range of variation management strategies (VMSs) on the cost-optimal electricity system composition in four regions with different pre-requisites for wind and solar power generation. The results add to previous work in defining how different variation management strategies match with specific electricity system contexts and provide guidance for policy makers considering VRE support as well as for actors which offer or invest in technologies with the purpose to manage variations.

It is found that absorbing (e.g. electric boilers) and shifting (e.g., demand-side management (DSM)) strategies increase the cost-optimal VRE investments if the VRE share is sufficiently large to reduce its marginal system value (system-limited), although they have a low impact on resource-limited VRE. In line with previous work, absorbing strategies are found to be more efficient at promoting wind power than shifting strategies, except in systems with large-scale hydropower. However, complementing strategies, such as low-cost biomass, are found to increase cost-optimal investments in wind power in systems with a low initial wind power share (resource-limited).

Furthermore, it is found that there are synergies between the variation management strategies, and while some VMSs reduce the value of another VMS (such as DSM and batteries in this work), a combination of VMSs can increase the cost-optimal investments in VRE more than the sum of the increases in VRE investments stimulated by individual strategies. These synergies were detected when VMSs of different categories (i.e., shifting, absorbing, complementing) are integrated into regions with moderate conditions for wind power and moderate-to-good conditions for solar photovoltaics.

Variation management strategies influence the cost-optimal investments in all types of generation, whereas the total annual electricity generation delivered by mid-merit generation and peak generation is not affected very much by the VMSs. Of the VMSs investigated, large-scale deployment of DSM reduces to the greatest extent the need for peak capacity. If 20% of the load can be delayed for up to 12 h, the investments in peak capacity are typically reduced by 30%–40%. For the regions investigated, VMSs consistently reduce the base-load investments.

Declaration of competing interest

There are no conflicts of interest.

Authors contributions

V.J. was responsible for acquisition of data and the manuscript draft. L.G. was responsible for the study conception and design as well as the critical review. Analysis and interpretation of results was shared equally between the authors.

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Appendix A. Description of the variation management strategies

Electric boilers

Electric boilers can increase the value of wind and solar power by adding to the electricity consumption during hours of high wind and solar generation. Thus, electric boilers, as investigated here, are assumed to be part of a district heating system where other heat generation sources are available. According to the classification suggested by Göransson and Johansson [2], electric boilers are here considered to be an opportunistic absorbing strategy. The impacts of electric boilers on cost-optimal investments are investigated for the two regions in which district heating systems are present (Hungary and southern Sweden) as shown in Table 1. The motivation for investing in electric boilers is the value obtained from the heat generated from low-cost electricity. The value of the heat in this work varies between seasons, as explained in the data section. No heat storage is assumed to be present in the systems. The value of the heat is included as a negative, time-step-dependent running cost for the electric boilers. The maximum demand from electric boilers is limited to 40% of the peak heat demand in winter and 20% of the peak during March, April, October and November. The peak district heating demand is 11 GW for southern Sweden (which is 63% of the total district heating capacity in all of Sweden) and 8 GW for HU [13].

Batteries

Two types of batteries are included in this work, lithium-ion batteries and flow batteries. The flow batteries are modelled with lower investment costs and longer life-times, as well as a lower power-to-storage capacity ratio (the C-factor, *CF*, is here assumed to be 0.25 for flow batteries, as compared to 0.5 for lithium-ion batteries) and lower round-trip efficiency (here assumed to be 0.7 for flow batteries and 0.9 for lithium-ion batteries). Thus, the lithium-ion batteries are suited to manage variations of higher frequency than the flow batteries. Batteries are implemented in the model with the Eqs. (C11)–(C14) in Appendix C.

Hydrogen storage

As explained at the beginning of the *Model* sub-section, this work assumes an industrial hydrogen demand that is supplied through electrolysis. To meet this demand, a certain level of investment in electrolyser capacity is required in all the cases. However, with an over-investment in electrolyser capacity and investments in hydrogen storage, the production of hydrogen can be distributed in time and thereby provide variation management in the form of a shifting strategy. Hydrogen with storage is however likely to act more as a combination of an absorbing and complementing strategy due to the low costs of storing hydrogen on a large scale. The hydrogen storage is implemented with an energy balance similar to that described in Eq. (C11) in Appendix C, although the battery charging is replaced by the operation of the electrolyser and the battery discharging is replaced by the hydrogen demand of the industrial sector. Thus, charging the storage is obviously limited by investments in electrolyser capacity. Hydrogen production and storage is assumed to have a total electrical efficiency of 62% (70% efficiency of electrolysis with additional losses from compression and storage) [29].

Low-cost biomass

Biomass-based generation can assume the role of a complementing strategy in a CO_2-neutral electricity system, and the model applied in this work includes possibilities to invest in biomass-fired steam plants (Biomass ST), coal and biomass co-fired plants with CCS (Bio-Coal CCS), biogas-fuelled gas turbines, and biogas-fuelled combined cycle gas turbines. However, biomass may compete with food production, and it is also identified as a key resource for decarbonising the industrial sector and the transport sector. This potential rush towards using biomass, together with a limited supply, may result in a significant increase in the price of biomass. In this work, we assume that biomass is available to the international market at 40 €/MWh. In the *Low-cost biomass cases*, biomass is instead available at 30 €/MWh.

DSM

DSM is implemented as the possibility to shift a given share of the load for up to a given length of time, as proposed by Göransson et al. [14], with complementary information from Zerrahn and Schill [15]. The implementation is depicted in Eqs. (C15)–(C20) in Appendix C.

Appendix B. Data

Table B1 gives the investment and running costs for the electricity generation technologies considered in the model. The investment costs and fixed operation and maintenance costs are based on IEA World Energy Outlook 2016 [16], with the exception of the costs for onshore wind power, which are based on the costs presented by Moné et al. [17] with a yearly learning rate of 0.4%. In the model, annualised investment costs are applied assuming a 5% interest rate. Technology learning for thermal generation is included as gradual improvement in the efficiencies of these technologies, reflected as a reduced running cost in Table B1. The running costs listed in Table B1 exclude the cost of cycling thermal generation. Instead, the start-up costs and part-load costs are included explicitly in the optimisation. The start-up costs, part-load costs, and minimum load level applied here are based on the report of Jordan and Venkataraman [18], in which all the technologies that employ solid fuels use the cycling costs given for large sub-critical coal power plants. The start-up fuel is, however, changed to biogas rather than oil in the present work. The cycling properties of nuclear power are based on the paper by Persson et al. [19], who describe a start-up time of 20 h and a minimum load level of 70%.

Biogas is assumed to be produced through the gasification of solid biomass, with 70% conversion efficiency. The cost of the

TABLE B1

Costs and technical data for the electricity generation technologies. The running costs in parentheses are for the low-cost biomass case.

Technology	Investment cost [M€/MW]	Running costs [€/MWh]	Fixed O&M costs [k€/MW,yr]	Life-time [yr]	Minimum load level [share of rated power]	Start-time [h]	Start cost [€/MW]
Biomass ST	1.86	82.6 (62.5)	50	40	0.35	12	240
Biogas CCGT	0.76	110 (89.9)	13	30	0.2	6	45
Biogas GT	0.38	183 (149)	8	30	0.5	0	0
Bio-coal CCS	3.46	36.7 (34.2)	113	30	0.35	12	240
Hydropower	2.06	1.0	47	500	0	0	0
Nuclear	5.15	18.9	154	60	0.7	24	660
Solar PV	0.60	1.1	10	25	0	0	0
Onshore wind	1.24	1.1	30	25	0	0	0
Offshore wind	1.84	1.1	100	25	0	0	0

TABLE B2

Full-load hours (FLH) and maximum capacity (Cap) limits for onshore wind classes 1–12, offshore wind, and solar PV.

Wind class and technology	ES3		HU		IE		SE2	
	FLH [h]	Cap [GW]	FLH [h]	Cap [GW]	FLH [h]	Cap [GW]	FLH [h]	Cap [GW]
1	960	0.4	1190	0.0	–	–	–	–
2	1550	3.6	1670	1.3	–	–	–	–
3	2020	12.0	2100	5.5	–	–	2030	0.6
4	2310	7.1	2370	7.8	–	–	2230	4.5
5	2560	6.1	2570	2.4	–	–	2440	6.9
6	2790	6.3	2750	1.3	–	–	2620	9.9
7	3020	4.6	3070	2.4	–	–	2900	9.1
8	3300	1.3	3350	0.2	–	–	3270	11.6
9	–	–	–	–	–	–	3700	1.5
10	–	–	–	–	4240	0.3	4120	1.7
11	–	–	–	–	4640	13.8	4600	0.5
12	–	–	–	–	5360	2.1	5260	0.1
Offshore	–	–	–	–	5360	...	5260	...
Solar PV	1770	24.7	1360	12.5	1000	9.6	1050	25.6

gasifier equipment is included in the form of 20 €/MWh added to the fuel cost, rather than being incorporated into the investment cost of the biogas technologies, since biogas is storable, which means that the gasifier equipment may attain a much higher number of full-load hours compared to the power plant consuming the biogas. The total cost of the gasification equipment is taken from Thunman et al. [20], and 8,000 full-load hours are assumed.

The wind power generation profiles are calculated for wind turbines with low specific power (200 W/m [2]), with the power curve and losses proposed by Johansson et al. [21]. The wind speed input data are a combination of the MERRA and ECMWF ERA-Interim data for year 2012, whereby the profiles from the former are re-scaled with the average wind speeds from the latter [22–24]. The high resolution of the wind profiles from the ERA-Interim data was processed into wind power generation profiles and put together into 12 wind classes for each region, for which the full-load hours (FLH) and the maximum capacities (Cap) for classes 4–12, as well as the offshore wind and solar PV are shown in Table B2. The wind farm density is set to 3.2 MW/km^2 and is assumed to be limited to 10% of the available land area, accounting for protected areas, lakes, water streams, roads, and cities [25].

Solar PV is modelled as mono-crystalline silicon cells installed with optimal tilt with one generation profile for each region. Solar radiation data from MERRA is used to calculate the generation with the model presented by Norwood et al. [26], including thermal efficiency losses. The full-load hours of solar PV in each region are shown in Table B2.

Hydropower is modelled for the region SE2 with one technology representing the local hydropower and a separate technology representing the hydropower imported from northern Sweden. Local hydropower has a capacity of 2.6 GW, whereas the capacity of the imported hydropower is constrained by the transmission capacity of 7 GW between northern and southern Sweden. The Swedish hydropower is coupled to reservoirs, and the ability to store energy is represented by an energy balance constraint over the reservoir of 2.5 TW h in total for the local hydropower and 7.7 TW h for the imported hydropower (30% of the total reservoir capacity in northern Sweden). The hydropower in-flow follows a weekly profile, with total annual in-flows of 12.3 TW h for local hydropower and 23.7 TW h for imported hydropower (corresponding to the total hydropower in-flow in northern Sweden reduced by the annual electricity demand in northern Sweden [27]). The flexibility of the plants is limited by historical limits on production increase and decrease [28], as proposed by Göransson and Johnsson [2].

The cost and technical data for VMSs are shown in Table B3 [29]. DSM is added exogenously to the system. The heat price is a simplification based on the modelled price for district heating

TABLE B3

Costs and technical data for the variation management technologies. The costs for electric boilers and electrolysers are given per MW and the costs of the batteries and hydrogen storage are given per MWh.

	Investment cost [M€/MW(h)]	Efficiency [%]	Fixed O&M costs [k€/MW(h),yr]	Life-time [yr]
Battery, Li-ion	0.15	90	25	15
Battery, Flow	0.18	70	13	30
Electric boiler	0.05	98	–	20
Electrolyser	1.0	62	20	10
H_2 storage	0.011	100	–	30

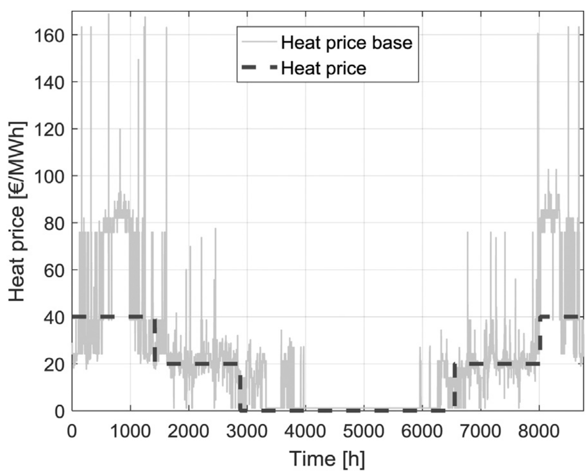

FIGURE B1

The dashed line gives the heat price used in the Electric boiler cases. The heat price is a simplification, based on the output (Heat price base) from a district heating model of Gothenburg.

in Gothenburg, as taken from Holm and Ottosson [30], who applied the model presented by Romanchenko et al. [31]. The price is modelled for Year 2032 and is shown together with the simplified cost descriptions in Figure B1. The heat prices of 40 €/MWh in winter-time and 20 €/MWh during the months of March, April, October and November are used in the *Electric boiler cases* in the analysis and are modelled as negative running costs.

Appendix C. The model

The model applied in this work is a cost minimizing regional investment model, which was first presented by Goransson et al. [11]. In this work it has been run with hourly resolution for a full year. Eqs. (C11)–(C20) are explaining the modelling of battery storage and demand-side management, which are a new addition to the original model. These new parts are therefore more thoroughly explained. The sets (upper case letters), parameters (italic upper-case letters) and variables (italic lower-case letters) for the Eqs. (C1)–(C10) are listed as:

P	The set of all technologies
T	The set of all timesteps
$\mathrm{P}^{\mathrm{VRE}}$	The subset of P which include the 12 onshore wind power classes, offshore wind power and solar PV
K	Set encompassing the timesteps k in the start-up interval.
C^{tot}	The total system cost
C_p^{inv}	The investment cost of technology p
i_p	The investments in technology p
$C_{p,t}^{run}$	The running cost of technology p in timestep t
$g_{p,t}$	The generation from technology p in timestep t.
$c_{p,t}^{cycl}$	The cycling cost (summed start-up cost and part load costs) of technology p in timestep t
D_t	Demand of electricity at timestep t
R_p	Capacity limit for investments in wind and solar resources.
$W_{p,t}$	The profile limiting the weather dependent generation.
$g_{p,t}^{active}$	The active capacity of technology p which is spinning and thus can generate electricity in timestep t
$L_p^{\min}$	The minimum load level of technology p
$g_{p,t}^{on}$	The capacity of technology p which is started in timestep t
$C_{p,t}^{on}$	The start-up cost of technology p in timestep t
$C_{p,t}^{part}$	The part load cost of technology p in timestep t
E^{cap}	The cap on carbon dioxide emissions
$E_{p,t}$	Emissions from technology p in timestep t
$E_{p,t}^{part}$	Part load emissions from technology p in timestep t
$E_{p,t}^{on}$	Start-up emissions from technology p in timestep t

The objective function of the model can be expressed as:

$$\min C^{tot} = \sum_{p\in P} C_p^{inv} i_p + \sum_{p\in P}\sum_{t\in T}(C_{p,t}^{run} g_{p,t} + c_{p,t}^{cycl}) \quad \text{(C1)}$$

The demand for electricity has to be met at all timesteps (see the updated demand constraint (C23)):

$$\sum_{p\in P} g_{p,t} \geq D_t, \forall t \in T \quad \text{(C2)}$$

Generation has to stay below installed capacity, weighted by profile, $W_{p,t}$, which is weather dependent for wind and solar power (but constantly equal to one for thermal technologies).

$$g_{p,t} \leq i_p W_{p,t}, \forall t \in T, p \in P \quad \text{(C3)}$$

Investments in wind and solar power cannot exceed regional resources capacity.

$$i_p \leq R_p, \forall p \in P^{VRE} \quad \text{(C4)}$$

Thermal cycling is accounted for by Eqs. (C5)–(C9) as follows:

$$g_{p,t} \leq g_{p,t}^{active}, \forall t \in T, p \in P \quad \text{(C5)}$$

$$L_p^{\min} g_{p,t}^{active} \leq g_{p,t}, \forall t \in T, p \in P \quad \text{(C6)}$$

$$g_{p,t}^{on} \geq g_{p,t}^{active} - g_{p,t-1}^{active}, \forall t \in T, p \in P \quad \text{(C7)}$$

$$g_{p,t}^{on} \leq i_p - g_{p,t-k}^{active}, \forall k \in K, p \in P \quad \text{(C8)}$$

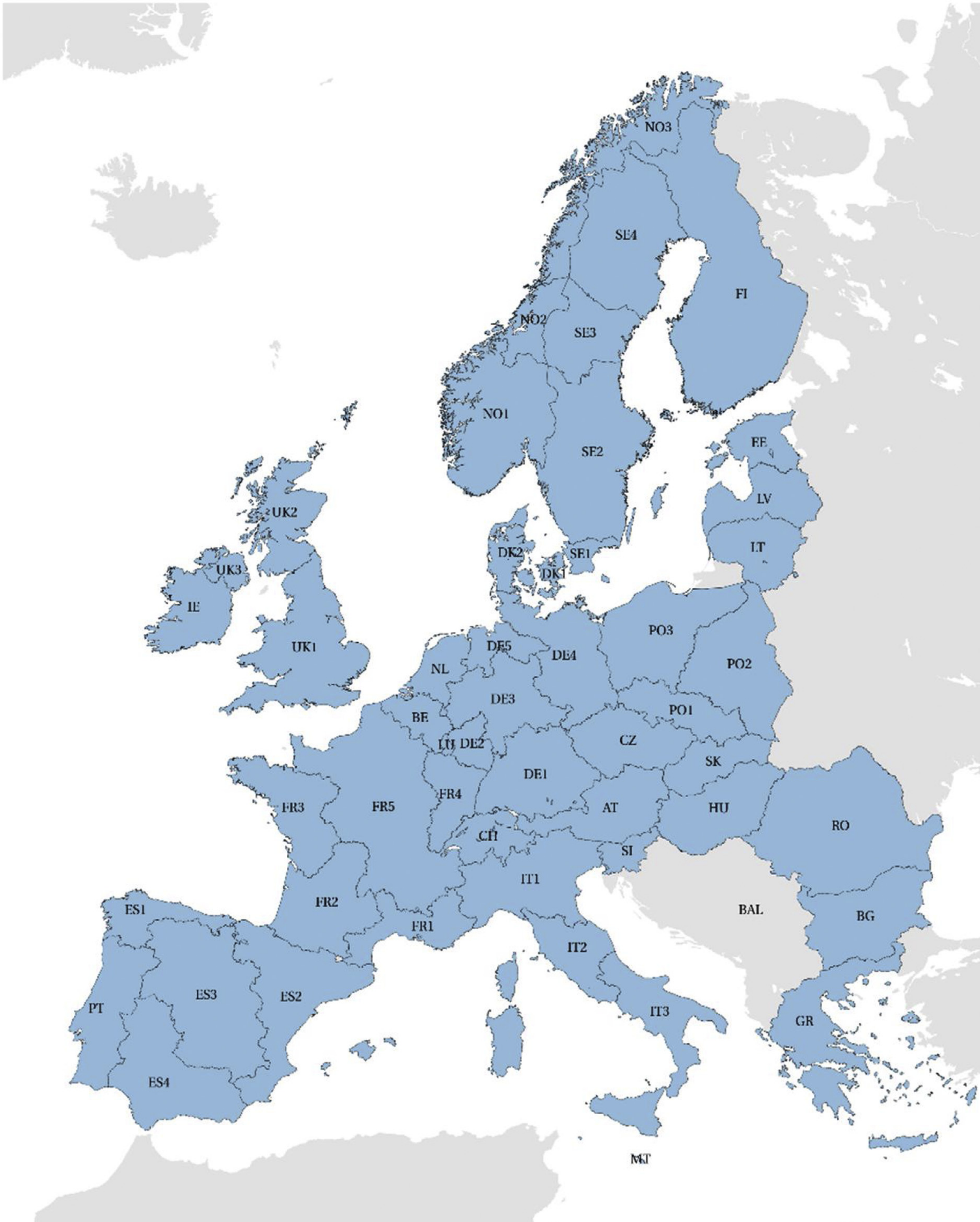

FIGURE B2

Map of the EPOD regions. The regions used in this work are ES3, HU, IE and SE2.

$$c^{cycl}_{p,t} \geq g^{on}_{p,t} C^{on}_{p,t} + \left(g^{active}_{p,t} - g_{p,t}\right) C^{part}_{p,t}, \forall t \in T, p \in P. \tag{C9}$$

Eqs. (C5) and (C6) limits the generation of a technology to lie between the hot capacity and the minimum load. Eq. (C7) controls the amount of capacity that is started and (C8) controls that capacity deactivated for at least the minimum start-up time. Eq. (C9) gives the hourly cycling cost for each technology.

The cap on total carbon dioxide emissions is constrained by:

$$\sum_{p \in P} \sum_{t \in T} \left(E_{p,t} g_{p,t} + g^{on}_{p,t} E^{on}_{p,t} + \left(g^{active}_{p,t} - g_{p,t}\right) E^{part}_{p,t}\right) \leq E^{cap} \tag{C10}$$

Batteries are implemented in the model with the following energy balance constraint for the batteries:

$$soc_{p,t+1} \leq soc_{p,t} + \eta_p b^{ch}_{p,t} - b^{disch}_{p,t}, \forall p \in P^{bat}, t \in T \tag{C11}$$

where $soc_{p,t}$ (state of charge) is the energy stored in the battery of technology type p and at time t, η_p is the round-trip efficiency of the battery, $b^{ch}_{p,t}$ is the electricity with which the battery is charged over the time-step considered, and $b^{disch}_{p,t}$ is the electricity delivered by the battery to the grid over the time-step considered. The charge and discharge volumes are limited by the investment in battery capacity and the power-to-storage capacity factor CF. Thus:

$$b^{ch}_{p,t} \leq i_p CF_p, \forall p \in P^{bat}, t \in T \tag{C12}$$

$$b^{disch}_{p,t} \leq i_p CF_p, \forall p \in P^{bat}, t \in T \tag{C13}$$

$$soc_{p,t} \leq i_p, \forall p \in P^{bat}, t \in T \tag{C14}$$

In addition, the amount of energy stored is, of course, required to be less than or equal to the battery storage capacity, as shown in Eq. (C14), and all the variables are stated with non-negativity constraints.

Similar to (C11) hydropower storage and hydrogen storage are modelled as is described in (C15) and (C16), respectively.

$$soc_{hydropower,t+1} \leq soc_{hydropower,t} + Inflow_t - g_{hydropower,t}, \forall t \in T \tag{C15}$$

where $soc_{hydropower,t}$ is limited by the current reservoirs and $Inflow_t$ is the hourly water inflow of energy to the reservoirs.

$$soc_{H2,t+1} \leq soc_{H2,t} + \eta_{electrolyser} prod_{electrolyser,t} - Demand_{H2,t}, \forall t \in T \tag{C16}$$

where $soc_{H2,t}$ is limited by the investment in hydrogen storage, $prod_{electrolyser,t}$ is the hourly electricity consumption in electrolysers which is limited by the electrolyser investments and $Demand_{H2,t}$ is the constant hourly demand of hydrogen.

DSM is implemented as the possibility to shift a given share of the load for up to a given length of time, as proposed by Göransson et al. [14], with complementary information from Zerrahn and Schill [15]. The implementation is depicted in Eq. (C17)–(C22). Eq. (C17) describes the cumulative demand, dh_t,on hold by delayed demand, dd_{t-l}, over the historical period from t and $L-1$ h back, where the length of the time-period, L, is set to 12 h in this work. Eq. (C18) limits the cumulative demand on hold to the demand served during the next L hours. The load balance is given by Eq. (C19). Eqs. (C20) and (C21) give the hourly limit imposed on delayed demand and served demand. The maximum delayed demand is given as a share, C^{dd} (here set to 20%), of the total demand for electricity in that hour, D_t. The maximum served demand is limited to a share, C^{ds} (here set to 30%), of the daily peak demand, D^{peak}_t. Eq. (C22) limits the risk of re-delaying the load.

$$dh_t \leq \sum\nolimits_{l=0}^{L-1} dd_{t-l}, \forall t \in T. \tag{C17}$$

$$dh_t \leq \sum\nolimits_{l=1}^{L} ds_{t+l}, \forall t \in T \tag{C18}$$

$$dh_t = dh_{t-1} + dd_t - ds_t, \forall t \in T \tag{C19}$$

$$dd_t \leq C^{dd} D_t, \forall t \in T \tag{C20}$$

$$ds_t \leq C^{ds} D^{peak}_t, \forall t \in T. \tag{C21}$$

$$dd_t + ds_t \leq \max\left\{C^{dd} D_t, C^{ds} D^{peak}_t\right\}, \forall t \in T \tag{C22}$$

The demand balance can now be updated with batteries, demand-side management and hydrogen demand as follows:

$$\sum_{p \in P} g_{p,t} + \sum_{p \in P_{bat}} bat^{disch}_{p,t} + ds_t \geq D_t + \sum_{p \in P_{bat}} bat^{ch}_{p,t} + dd_t + prod_{electrolyser,t}, \quad \forall t \in T. \tag{C23}$$

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