Short-Term Demand Response Of Flexible Electric Heating Systems: The Need For Integrated Simulations

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Short-term demand response of flexible electric heating systems: the need for integrated simulations

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Abstract—Active Demand Response (ADR) can contribute to a more (cost-)efficient operation of and investment in the electrical power system as it provides the needed flexibility to cope with the intermittent character of renewables. One of the promising demand side technologies in terms of ADR are electric heating systems as they allow to modify their electrical load pattern without affecting the thermal energy service they deliver, due to the thermal inertia in the system. However, these systems are hard to describe with traditional demand side models, since the performance depends on boundary conditions (occupants behaviour, weather conditions). Therefore, in this paper, an integrated system approach is applied, taking into account the dynamics and constraints of both electricity supply and heating systems. Only such an integrated system approach is able to simultaneously consider all technical and comfort constraints present in the system. The effects not captured by traditional approaches – such as price elasticities and virtual generator models – are identified and quantified, enabling the reader to select a modelling approach, weighing the computational effort against the required accuracy. In extensive power system studies, this approach can be used to assess the technical potential and all effects of flexible demand side technologies.

Index Terms—Active Demand Response, Integrated Models, Electric Heating Systems

I. INTRODUCTION

Demand side management (DSM) is a (market) concept that actively uses options at demand and supply side to modify electricity demand to increase customer satisfaction and coincidentally produce desired changes in the electric utility’s load shape [1]. If applied correctly, DSM could come with a variety of benefits, such as a reduced electricity generation margin, higher operational efficiencies in production, transmission and distribution, more effective investments, lower price volatility, lower electricity costs and the possibility to manage highly intermittent renewables (see, amongst others, [2]–[4]). In this paper, the focus is on short-term load shifting, one of the aspects of DSM, which will be referred to as Active Demand Response (ADR) [1].

ADR can be facilitated by dispatchable load programs (direct load control, curtailable load, demand bidding) and/or price-based programmes (real-time pricing, time-of-use pricing, peak pricing), each with its own opportunities and drawbacks. However, residential consumers are generally not willing to forfeit the foreseen end-use of the electrical energy as the benefits they perceive (e.g. a lower electricity bill) do not outweigh the drawbacks. Some demand side technologies though contain some form of (virtual) storage, which can be used to affect the electrical load pattern perceived by the electrical power system without tampering with the quality of the energy services provided. Typical residential examples are thermostatically controlled loads – such as boilers, heat pumps, refrigerators and air conditioners – and plug-in electric vehicles [3]. The storage allows these loads to simultaneously be fully responsive and non-disruptive in terms of the perceived energy service [3].

However, many challenges remain to be overcome before a large scale roll-out of flexible demand side technologies will emerge. One of these challenges is the quantification of the benefits – for consumer and producers – of ADR programmes [2]. Even though many studies include or even focus on ADR, often the supply side or the demand side is represented too simplistically. When the focus is on electric power generation, the demand is represented via a price elastic demand or via virtual generator models [5]1. Looking at the demand side, a price profile is typically used to represent the supply side [6]–[8]. All of these modelling techniques (see Section II) have proven their merits, but are inadequate to study the true interaction between supply and demand side, especially when storage type customers are involved. In this paper, a modelling framework based on a system approach is introduced that can be used to correctly identify these effects. A physical model of the demand side technology will be integrated in a traditional unit commitment model (see Section III).

The need for integrated simulations and their added value in system studies is illustrated in a methodological case study – flexible electric heating systems – but other demand side technologies can be incorporated through the same methodology. The electric heating systems considered in this paper consist of heat pumps and auxiliary electric resistance heaters that provide both domestic hot water (DHW) and space heating (SH) via a floor heating system. This system is designed to guarantee a certain thermal comfort level (e.g. a certain range on indoor temperatures and hot water when desired) and is characterised by large thermal inertia. Thermal energy storage is provided via the hot water storage tank, the thermal mass of the building and the floor heating system. As these small scale systems can be installed in large numbers and control access to these loads could be very inexpensive with the advent of communication platforms, they are good candidates for ADR [3].

Based on the optimization results from the proposed integrated model, this paper will demonstrate that neither a price-

1The virtual generator models (VGM) are denoted as ‘dispatchable load models’ by De Jonghe. In this paper, VGM is used to stress the similarity between the constraints on the demand side technology and those employed to describe a generator.
elasticity, nor a virtual generator model can fully describe the effects of flexible electric heating systems on the electric power system. Furthermore, results based on a demand side model cannot be extrapolated to calculate system-wide effects as they fail to describe the feedback of demand response on the supply side. These conclusions hold especially for storage type customers where the storage losses are hard to model, such as thermal loads. The analysis presented should allow the reader to decide what kind of model he needs, weighing the computational complexity against the desired accuracy.

The remainder of this paper is organized as follows. Firstly, the literature on demand and supply side modelling is reviewed in Section II. Secondly, the model and data employed in this paper are briefly presented in Section III. In the fourth section, the inadequacy of price-elasticities, virtual generator models and models with a focus on the demand side to describe demand response of heating systems is demonstrated. The final section summarises the conclusions and elaborates on possible future work.

II. LITERATURE STUDY: MODELLING ADR

The focus of this literature review is on the various modelling techniques used to study the effects of price-responsive or flexible users. A first group of models are those with a focus on the supply side (Section II-A). Secondly, the models with a focus on the demand side are briefly discussed in Section II-B. Recently, some authors have integrated physical models of demand side technologies and power system models. A short review can be found in Section II-C, together with a discussion on the added value of the model developed in this paper (Section II-D).

A. Models with focus on the supply side

To study power system-wide effects of flexible consumers, most researchers employ typical unit commitment and economic dispatch models, extended with an aggregated representation of the flexibility in demand. In general, two main representations of the flexible demand side can be identified: price-elasticities and so-called virtual generator models (VGM).

1) Price-elasticity based models: In market models, the price responsiveness of consumers can be represented via a price-elasticity. These elasticities are a measure of the change in demand in response to a change in the price of electricity. Own-elasticities represent the change in consumption as a reaction on a price change in that same time step, while cross-elasticities are used to describe demand changes due to price changes in other hours [5]. The (assumed range of) elasticities used in these models typically stem from analyses of historical data [5].


2) Virtual generator models: Virtual generator models (VGM) are used to represent the technical limitations of the demand side technology. The demand is modelled as a electricity generating unit with a negative output. Demand reductions and shifts can be constrained in amount, time and ramping rate. Electrical energy storage and possible losses, e.g., via a demand recovery ratio – see Section IV-B, can be incorporated. The constraints can be based on observations or detailed physical models. The VGM is dispatched similarly as a conventional generating unit and therefore often referred to as direct load control [5].

Su & Kirschen [13] developed a VGM model, based on the marginal benefit a consumer experiences from the consumed electrical energy, to analyse scheduling of generation when demand is flexible. Karangelos & Bouffard [14] investigated the benefits of demand side participation in the provision of ancillary services. The demand response is limited via ramp rates, power limits and in its demand recovery. Tan & Kirschen [15] have studied the effect of ADR on reserves in electricity markets. The demand side participation in the reserve market is modelled via a VGM, solely constrained by power limits. Paulus & Borggreve [16] have estimated the technical and economical potential of energy-intensive industries – modelled as energy storage facilities – to participate in electricity and balancing markets in Germany.

Dietrich et al. [17] applied both a VGM-type model and a model based on price-elasticities to study the impact of ADR in an electrical power system with a high penetration of wind energy. Similarly, De Jonghe [5] studied operational effects and optimal investment decisions via VGM- and elasticity-based models.

B. Models with focus on the demand side

Specific thermal energy storage (TES) systems are designed to allow for ADR, as thermal energy is more easily stored than electrical energy. As denoted by Arteconi [18] a large range of TES technologies exist and are in use as ADR technology. In addition, some thermal systems allow for thermal storage without installing specific TES. Hewitt [19] studied the use of the built environment – i.e., its thermal inertia – as a TES, in the case of a heat pump delivering space heating and domestic hot water (DHW). Hewitt found that both the building and the hot water tank are possible candidates for ADR. Furthermore, Hewitt [19] states that when one studies the benefits for the consumers and generators under ADR, one must take into account the dynamics of both the demand and supply side. However, when assessing the potential of a thermal system for ADR, most authors start from a fixed electricity price profile [6]–[8] to determine how much the electrical load pattern can be modified. The authors typically conclude how much the electricity cost can be reduced for the owner of the system, but do not consider a feedback of the shifted electrical load pattern on the electricity price. Other authors, such as Nyeng [20], consider using a constant electricity price signal to assess the potential of electric heating systems for load shifting.
C. Integrated simulations

Recently, a number of authors have developed integrated models. Both demand and supply side are represented by physical models and jointly optimized. A group of researchers at the university of Victoria (Canada) have recently published a number of papers [21]–[26], inspired by the work of Callaway [27], that are closely related to work presented in this paper. They studied comfort-constrained distributed heat pump management and intelligent charging of electrical vehicles as balancing services, with a particular focus on balancing wind power, as a spinning reserve resource and as a voltage stabilising measure. The physical models of the heat pumps and electric vehicles are integrated in a linear representation of the supply system. Hedegaard et al. [28] developed an integrated model, including different types of TES and heat pumps, to assess the potential of ADR to balance wind power. The results should be interpreted with caution, as the level of detail in the thermal model is limited (e.g. thermal losses are not temperature dependent).

These integrated models incorporate both the dynamic behaviour of the supply side and of the heating systems on the demand side. This approach offers a number of advantages. Firstly, the electricity demand from the thermal systems is closer to reality, since it allows to take into account the occupants behaviour, the weather conditions and the physical behaviour of the considered heating systems and dwellings. Secondly, all (feedback) effects of electrical load redistribution – on demand and supply side – are represented correctly. For example, the losses (electrical and thermal) associated with load shifting can be precisely determined. Thirdly, it allows to identify the technology that was used to perform the electrical load shifting. This allows to study and compare the impact of multiple flexible demand side technologies. Lastly, it ensures the end-use functionality of the demand side technology, while simultaneously ensuring the availability of e.g. the balancing services provided by ADR on the supply side.

D. Added value of this paper

The main contribution of this paper is twofold. Firstly, in terms of modelling, it improves the approach by Williams et al. [21] by incorporating a more detailed representation of the demand side (occupant behaviour, technology and thermal behaviour of the dwellings) and by expanding the linear model of the supply side to a more realistic mixed integer model. The latter allows to incorporate start-up and shut-down costs & constraints – dynamics of the supply side that will be affected by ADR, as shown by [17] – while the former allows to incorporate solar and internal gains. As shown below, solar and internal gains are a non-negligible part of the thermal power supplied to the dwellings. Secondly, as these integrated models become computationally costly to solve, the effects which are difficult to capture in simulations based on price-elasticities, VGM or demand side models are illustrated. This should enable the reader to decide which modelling technique he needs, weighing the computational effort against the desired accuracy level.

III. INTEGRATED MODEL - A MODEL FOR DEMAND AND SUPPLY SIDE

The discussion of the integrated model is split up into two parts. Firstly, the model itself is described in Section III-A. Secondly, the data and assumptions used in the presented methodological case study are discussed in Section III-B. A full description of the integrated model and case study data can be found online [29].

A. Model description

The integrated model describes an optimisation problem, in which the overall operational cost of the electricity generation is minimised, subject to technical and comfort constraints of both the supply and the demand side. This mixed integer linear programming (MILP) model combines a unit commitment (UC) and economic dispatch (ED) model on the supply side with a detailed representation of the physical – thermal and electrical – behaviour of the considered demand side technology. The model is implemented in GAMS 23.7 and MATLAB® 2011b. CPLEX 12.5 is used as solver.

Via the UC and ED model, the commitment status and hourly output of each power plant are determined so that the electricity demand is met at the lowest overall operational cost, taking into account the technical constraints of the power plants. These constraints include the minimum and maximum output, the ramping rates and minimum on and off times of each power plant. The operational cost consists of fuel, emission and start-up costs. In the integrated model, the demand for electricity that needs to be met consists of two parts: a fixed electricity demand profile and the electricity demand from the flexible demand side technology. The latter electricity demand is an optimisation variable, determined through the demand side model.

This demand side model describes – in this case study – the physical behaviour of the electric heating systems, which deliver heat for domestic hot water production and space heating. The thermal behaviour of the house, floor heating system and domestic hot water storage tank is modelled through a linear state space model [29]. This model allows to convert a certain demand for thermal comfort in a demand for electric power for each dwelling. Summing and scaling these demand profiles allows to simulate a certain market penetration of flexible heating systems. Flexibility is procured via thermal energy storage in the building shell, the floor heating system and the hot water storage tank. The constraints on the thermal comfort required by the occupants – e.g. temperature constraints and the availability of hot water – results in constraints on the electrical power demand and on the flexibility offered to the supply side.

In this integrated model, it has been assumed that demand and supply are controlled centrally. This abolishes the need to set up a real-time pricing system. However, if the price signal used in such a real-time pricing system would correctly reflect the cost of electricity, the demand and supply side would interact as obtained from the integrated model (see Section IV-C).
B. Methodological case study

Demand for electricity is met through renewable energy sources (RES) and conventional generation. Electricity feed from RES is treated as a demand correction and can be curtailed if this yields a lower system cost. The conventional generation capacity is used to balance the residual electrical load. In terms of installed conventional capacity (10 GW in total), coal (3 units), lignite (3 units) and gas fired capacity account for 24% each. The gas fired capacity consists of 4 simple gas turbines (4%) and 5 combined cycle gas turbines (20%). Nuclear capacity accounts for another 24% of the installed capacity (2 units). The remaining 4% is liquid fuel fired capacity (4 units). The technical characteristics of the power plants, the costs of the various fuels and their carbon content are listed in [29].

The fixed demand profile used is based on hourly demand data for Germany for 2010 [30]. The week with the total energy consumption closest to the yearly average is selected. The profile is preserved and scaled to equal 90% of the peak power of the supply system. If variable demand is present, the resulting demand profile is rescaled to represent a certain percentage of the total electrical energy demand. RES feed data are provided by the German TSO’s [31]–[34]. The week with the total RES energy in-feed closest to the weekly average value for 2010 has been selected. The profile is preserved and rescaled to satisfy a certain percentage of the total energy demand of that week. To limit calculation times, only the first 48 hours of both profiles are retained.

The variable demand stems from 25 identical dwellings. Each residence is modelled as a detached house with a floor area of 75m² and equipped with a floor heating system. The demand for space heating (SH) and domestic hot water (DHW) is met through an air coupled heat pump equipped with an auxiliary electrical resistance heater. Each house is equipped with an additional auxiliary electrical resistance heater for space heating. The state space model of these buildings was developed by Van Oevelen [35], Solar heat gains were determined using the model of Baetens et al. [36]. The model for the heat pump was developed by Verhelst [8]. The demand for hot water is based on Peuser et al. [37]. The comfort constraints, thus the electricity demand, differs as the occupancy (based on Richardson et al. [38]) and the number of occupants differs in each dwelling.

IV. RESULTS AND DISCUSSION: THE NEED FOR INTEGRATED SIMULATIONS

One of the main advantages of an integrated model is the correct representation of the interaction between supply and demand, while taking into account the dynamics and physical constraints on both sides. In this section, this feature is demonstrated by comparing the results of the integrated models with three classical approaches (see Section II) to describe this interaction. Firstly, price elasticities are calculated ex-post (Section IV-A). Secondly, the difficulties in developing a correct VGM representation are discussed (Section IV-B). Thirdly, the impact of the assumed fixed electricity price (profile) in demand side models is elaborated in Section IV-C.

A. Price-elasticities are insufficient to describe the DR of storage type customers

As outlined in Section II, many studies on demand side flexibility use price-elasticities to describe the price responsiveness of flexible customers. The elasticity is defined as:

\[ \epsilon_{u,k} = \frac{\partial d_u}{\partial p_k} \frac{p_{0,k}}{d_{0,u}} \]  

with

- \( p_k \) the price of electrical energy in hour \( k \),
- \( d_u \) the demand for electrical energy in hour \( u \)

The index 0 indicates the initial or anchor electricity demand and price levels. If \( k \) equals \( u \), the elasticity is referred to as the own-elasticity of the demand. Cross-elasticities \( (k \neq u) \) indicate the change in demand for electricity in hour \( u \) in response to a change in the price of electricity in hour \( k \). Cross-elasticities are needed as consumers are generally not willing to solely reduce their demand, but are more likely to redistribute some of their demand - shifting it away from peak price to low price periods. This redistribution may even yield a higher overall electricity consumption and cannot be captured by own-elasticities alone. Price elasticities are a powerful tool to capture the price responsiveness of many customers. However, as shown below, these elasticities are not suited to describe the responsiveness of storage type customers when storage is accompanied by losses not linearly dependent on the energy stored or the power supplied, such as thermal systems.

To calculate the price-elasticity matrix of the flexible electrical demand, represented physically by the electric heating systems, the following methodology has been adopted. Firstly, the reference price\(^2\) and electricity demand levels are selected.

\(^2\)The electricity price as perceived by the electric heating systems is here calculated as the dual value of the market clearing condition. In the MATLAB®-GAMS coupling [40], this dual value is calculated by fixing the integer values (after optimisation) and solving the resulting linear program. As such, the electricity price is not necessarily set by the most expensive active unit. Furthermore, this approach does not incorporate start-up costs of additional units: if all active units are running at full capacity, the most expensive unit will set the electricity price.
In this case, the electricity prices and the optimised electricity demand levels of the simulation with 25% RES will provide the anchor points of the elasticity curve (Fig. 1). Secondly, as the elasticity matrix consists of 48x48 unknowns, at least 48 new optimisations had to be performed. In these optimisations, the share of renewables is varied between 0 and 50%. These optimizations provide 48 new electricity price and electricity demand vectors: due to a different share of RES, the consumers will see different electricity price levels as the supply curve changes. The electricity price and electricity demand levels allow to calculate an approximation of the price-elasticity matrix via:

$$\epsilon^{48x48} = [\Delta d] \cdot [\Delta p]^{-1}$$  

(2)

Each column in matrices $[\Delta d]$ and $[\Delta p]$ is calculated from one of the 48 optimisations as the difference between the observed electricity price (demand) and the anchor values in each hour, normalised with respect to the anchor price and demand levels.

In Fig. 2a, the erratic behaviour of the observed price-elasticity over the two studied days is shown. In the system under consideration, 10% of the demand stems from flexible electric heating systems\(^3\). Neither the own-elasticities, nor the cross-elasticities can be correlated to the observed prices, the residual electrical demand (see Fig. 2b), the thermal power supplied to the heating systems or the thermal energy stored in the system (see Fig. 3). The erratic fluctuations of the price-elasticity over time, combined with the absence of any correlation to known systems variables (e.g. the residual demand), make the price-elasticity almost impossible to predict. Furthermore, note that the elasticities are large compared to those found in the literature [5]. Partly, this can be explained by the central control approach (or direct load control) adopted here, which should be considered as the maximal technical potential in terms of flexibility, yielding higher elasticities [12]. These results show the need for an alternative modelling approach for ADR, such as the presented integrated model.

\(^3\)If the heat pumps would face a flat tariff, they would be responsible for 10% of the total electrical energy demand over the simulated period (the ‘design share variable demand’). The individual customers will minimise their own electricity consumption. In the cases where the heat pumps face real-time electricity pricing, their electricity consumption will generally be higher. Electricity consumption is shifted to low price periods and the energy is stored in the thermal mass of the building or the storage tank. These systems are however characterised by thermal losses and thus yielding a higher electrical energy consumption, but at lower overall system cost.
A flexible demand can be modelled through a virtual generator model (see Section II). In essence, the demand is described as a generating unit with a negative output and a set of constraints on this output. The limits on the output of the virtual generating unit (electrical power) can easily be deduced from the nameplate capacity of all electric heating systems involved on the demand side. Ramping limits are not required in this case as the demand side technologies can ramp up and down well within the hour - the time step of the simulations. Some demand side technologies may however exhibit time constants larger than those of the electrical power system and thus require ramping limits. For example, chemical plants typically require several hours to adapt their electricity consumption. Similar reasoning applies for the limits on on- and off-times. For the description of storage type customers, constraints are required on the storage capacity, which typically consist of a loss factor (or efficiency), combined with a minimum and maximum energy limit for the storage capacity. These parameters are easily quantified for some flexible loads with storage, such as electric vehicles. These calculations however become rapidly more complex as one moves to loads with thermal energy storage, as shown below.

The state of charge of a storage system at a certain time step is typically modelled based on the previous state, the withdrawal and the addition of energy at that time step. In Fig. 3a, the average thermal energy content of a house, confined in the building envelope and the hot water storage tank, is shown over the course of the two days. The minimum and maximum thermal energy levels can be interpreted as the comfort limits, depending on the user behaviour and required temperatures, and thus vary with time. Looking at the thermal power supply (Fig. 3b), the importance of solar and internal heat gains is striking. Neglecting to model these user and temperature dependent gains would yield a significantly lower state of charge, which in turn may result in an overestimation of the electricity demand via a VGM. In reality, this may lead to a violation of the comfort constraints on the consumers end. The thermal losses are not only temperature and time dependent, but are also dependent on user behaviour (consumption of hot water, occupancy profiles) and weather conditions (ambient air temperature, solar heat gains). In conclusion, the description of the state of charge and the thermal energy limits of a demand side thermal energy storage system requires detailed knowledge of the state (temperatures) of and disturbances imposed on that storage system.

The importance of a correct representation of the thermal losses at the demand side technology is illustrated in Fig. 4. The demand recovery ratio \( DRR \) behaves erratic with respect to the design share of variable demand and renewable energy in the system. The \( DRR \) is higher for lower penetration levels of demand response in the system. As more consumers become price responsive, the \( DRR \) converges.
energy use of those heating systems\textsuperscript{4} [5]. Fig. 4 shows that in general the DRR is higher for lower penetration levels of demand response and renewable energy in the electrical power system. As more consumers become responsive, the DRR converges. Thus, the behaviour of the flexible electric heating systems is not only dependent on the consumers themselves, but also on the boundary conditions under which they operate: the amount of renewable energy in the system and the behaviour of the other consumers. Note that this effect is mainly important if one is looking at the consumer side. For example, if 20% of the electricity demand is flexible, the difference in the total demand for electrical energy due to the (incorrect representation of) thermal losses of demand side energy storage will remain below 2%.

C. The importance of price signals in demand side models

The potential of a flexible demand side technology is typically assessed by assuming a fixed electricity price profile. These studies lack to identify the feedback between the demand side technology and the electricity price (supply side). If one consumer shifts his electricity demand to a moment with lower electricity price, this will not affect the electricity price at that moment. If thousands of consumers shift their electricity demand to that moment, this can increase the electricity price at that moment, making load shifting less interesting.

This effect was identified in the integrated model. Fig. 4 shows the increase in electricity consumption compared to non-responsive heating systems\textsuperscript{4}. As more load shifting occurs, some parts of the thermal system typically attain higher temperatures, leading to an increase in thermal losses and a higher electricity consumption [6]–[8]. Because typical demand side models do not take into account the feedback between their electricity use and the electricity price, the DRR would remain constant, no matter how much the market penetration of this flexible demand would be. The results shown in Fig. 4 clearly demonstrate that this assumption is not correct.

It can be verified that the electricity price profile obtained from the integrated optimisation, when used in a cost minimisation model of non-responsive heating systems\textsuperscript{5}, will yield a similar electricity demand profile and cost for consumers. Moreover, when this electricity demand profile, augmented with the fixed electricity demand profile, is entered in a supply side model, it will result in an overall system cost equal to that of the co-optimisation. This result allows for multi-scale analysis: based on simple demand side models in an integrated model, a electricity price profile that correctly represents the actual hourly cost of electricity can be obtained, which is an essential input parameter for detailed simulation models of that demand side technology.

\textsuperscript{4}When the heating systems do not interact with the electricity generation system, an optimisation towards minimum electrical energy use is performed at the demand side. The DRR will therefore always be greater than or equal to 1. See also footnote 4.

D. The importance of optimality

As the proposed model is computationally costly to solve, relative optimality gaps up to 2% are tolerated in the presented results. Convergence is slow and might be due to a poor estimate of the lower bound on the optimization. This is however not of importance for the discussion of the effects illustrated in this paper, but becomes key if one moves to the interpretation of the absolute values of e.g. the system cost (the objective value), CO\textsubscript{2}-emissions or other optimization variables. The origin and the impact of the optimality gap is still unclear and subject of future research.

V. Conclusion

Active Demand Response (ADR) could lead to a variety of benefits, such as a reduced electricity generation margin, higher operational efficiencies in electricity production, transmission and distribution, more effective investments, lower price volatility, lower electricity costs and the possibility to manage highly intermittent renewables. Correct quantification of these benefits is one of the main challenges that need to be overcome before a large scale roll-out of flexible demand side technologies can take place.

This paper shows the need for integrated simulation of both supply of and demand for electricity in order to correctly assess the interaction of flexible electric heating systems with the electricity generation system. The added value of this modelling approach was illustrated compared to three other models used to study this interaction: price-elasticity based models, virtual generator models and demand side approaches. When the demand side technology contains energy storage, with losses dependent on the state of, and boundary conditions imposed on, the system; the integrated simulation showed effects which cannot be fully captured with the models in the literature. Examples are the change in electricity use at one time step due to a change in generation in another time step while maintaining consumer comfort, the impact of solar and internal heat gains on the electricity demand and the decrease in load shifting when the flexible heating systems attain a large market penetration.

Multiple expansions of the model can further strengthen this research. Firstly, the origin and the impact of the optimality gap on the results is still to be investigated (see Section IV-D). Secondly, as denoted in Section I, other technologies besides heating systems can also be used for ADR, such as electric vehicles and deferrable loads, but also pumped hydro storage. Integrating all these systems into one model would allow competition between these various means of flexibility. Thirdly, the inclusion of uncertainties on RES, ambient temperature and user behaviour would make the model more realistic. Fourthly, at the supply side, inclusion of a reserve market (with demand side participation) and a transmission grid would be interesting. Fifthly, the aggregation of consumers presented in this paper is simplistic, as the goal was merely to show the need for integrated simulations. However, for impact studies, simulations should be carried out with more realistic representations of the population, the climate and building stock.
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