Integrated modeling of active demand response with electric heating systems

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Abstract

Active Demand Response (ADR) can contribute to a more cost-efficient operation of, and investment in, the electric power system as it may provide the needed flexibility to cope with the intermittent character of some forms of renewables, such as wind. One possibly promising group of demand side technologies in terms of ADR are electric heating systems. These systems could allow to modify their electrical load pattern without affecting the final, thermal energy service they deliver, thanks to the thermal inertia in the system. One of the major remaining obstacles for a large scale roll-out of ADR schemes is the lack of a thorough understanding of interactions between the demand and supply side of the electric power system and the related possible benefits for consumers and producers. Therefore, in this paper, an integrated system model of the electric power system, including electric heating systems subjected to an ADR scheme, is developed, taking into account the dynamics and constraints on both the supply and demand side of the electric power system. This paper shows that only these integrated system models are able to simultaneously consider all technical and comfort constraints present in the overall system. This allows to accurately assess the benefits for, and interactions of, demand and supply under ADR schemes. Furthermore, we illustrate the effects not captured by traditional, simplified approaches used to represent the demand side (e.g., price elasticity models and virtual generator models) and the supply side (e.g., electricity price profiles and merit order models). Based on these results, we formulate some conclusions which may help modelers in selecting the approach most suited for the problem they would like to study, weighing the complexity and detail of the model.

Keywords: Demand Side Management, Active Demand Response, Integrated Models, Electric Heating Systems

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1. Introduction

Demand side management (DSM), in the broad sense, entails all those actions aimed at modifying the electricity demand to increase customer's satisfaction and coincidentally produce the desired changes in the electric utilities load in magnitude and shape [1]. If applied correctly, DSM could come with a variety of benefits, such as, but not limited to, (1) a reduced electric power generation margin commonly used to deal with peak demands; (2) a higher operational efficiency in production, transmission and distribution of electric power; (3) more effective investments; (4) lower price volatility; (5) lower electricity costs and (6) a more cost-effective integration of highly intermittent renewables [2–4]. In the literature, three broad categories of DSM are identified: energy efficiency and conservation, on-site back up through local generation or storage and demand response [3]. Active Demand Response (ADR) is defined as 'changes in electric usage implemented directly or indirectly by end-use customers/prosumers from their current/normal consumption/injection patterns in response to certain signals' [5]. In this paper, the focus is on ADR, and particularly on short-term load shifting, by means of thermal storage in the building stock.

ADR can be facilitated by incentive-based programs (direct load control, curtailable load, demand bidding) and/or price-based programs (real-time pricing, time-of-use pricing, peak pricing), each with its own opportunities and drawbacks [6]. Gils has identified a large potential for ADR of flexible loads in Europe, mainly in countries with significant amounts of electric heating and air conditioning [7]. 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. Fortunately, some of these demand side technologies contain various forms of storage, which can be used to affect the electrical load pattern seen by the electric power system without compromising the quality of the energy services provided to the end-consumer. Typical residential examples are thermostatically controlled loads (such as boilers, heat pumps, refrigerators and air conditioners), plug-in electric vehicles and deferrable loads, namely laundry machines and dish washers [8]. Their inherent 'energy storage'[1] allows these loads to simultaneously be fully responsive and non-disruptive in terms of the perceived energy service. In this setting, the role of thermal energy storage (TES) as an ADR enabling technology is often investigated. As denoted by Arteconi et al. [9] a large range of TES technologies exists and is in use for ADR purposes. The built environment can even allow for thermal storage without installing specific TES [10]. Small scale electric heating systems can be installed in large numbers in the built environment and control access to these loads could be very inexpensive with the advent of communication platforms; so they are good candidates for ADR [8, 11].

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 related to the technical obstacles preventing price signals from being properly transferred to the customers [12], while others are related to the quantification of the benefits for consumer and producers under ADR programs [2]. In order to quantify the effects of introducing such programs, the assessment of the interaction between supply and demand side is of paramount importance. Many models however still fail to incorporate the interactions between demand and supply in ADR programs. In Fig. 1 a conceptual schematic of the interdependence of the demand side and the supply side (models) is shown: the electricity price profile, typically the result of a supply side model, is a necessary input to the demand side model, while the demand for electric power, output of the demand side model, is a necessary input of the supply side model. In short: the electricity prices change with the demand for electric power and vice-versa. In light of this challenge, we develop integrated system models that tackle this issue. As we will show later in this paper, this is the only way one can capture this interaction to its full extent.

Nevertheless, even though many studies deal with, or even model, ADR, often the supply side or the demand side are represented simplistically. When the focus is on electric power generation, most researchers employ typical unit commitment (UC) models and economic dispatch (ED) models[2], extended with an

[1] In the strict sense, no energy is stored. One can only shift the load of these appliances in time, decoupling the energy service (e.g. heating) and the load as seen by the electric power system in time.

[2] A UC model aims to schedule the most cost-effective combination of power plants to meet the demand for electric power. The ED model determines the production levels of each unit on the basis of the least cost usage of the committed assets.

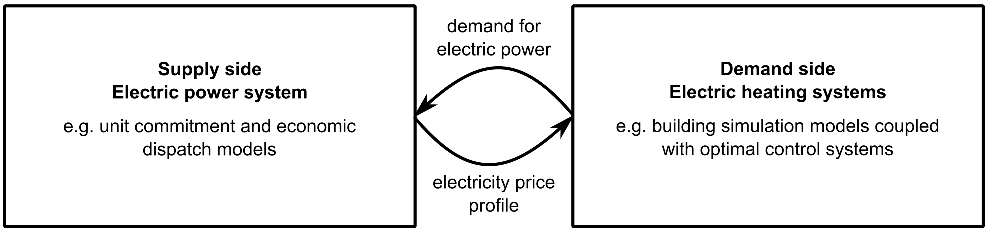


Figure 1: Conceptual schematic of the interaction between the supply side (i.e., the electric power system, typically represented via unit commitment and economic dispatch models) and the demand side (here electric heating systems, typically studied via building simulation models with optimal control systems).

aggregated representation of the flexibility in demand. Two typical representations of the flexible demand side are considered in this paper: price-elasticity models [13–17] (Section 2.1) and so-called virtual generator models (VGM) [18–21] (Section 2.1). In contrast, in studies which are focused on the energy demand of buildings, researchers often take the supply side of electricity into account by considering a (fluctuating) electricity price [22–27]. This is discussed in Section 2.2. Although all of these modeling techniques have proven their merits, they are inadequate to study the true interaction between the demand side and the supply side under ADR, especially when storage-type customers are involved. Recently, some authors [11, 28–35] proposed integrated models of both the supply of, and demand for, electric power, as discussed in Section 2.3. The reference model presented in this paper falls in this last category.

The purpose of this paper is to illustrate the relevance of using an integrated model to study ADR, involving the interaction between the supply side and the demand side, building further on the work presented in [36]. To this end, a modeling framework based on a system approach is introduced: a physical model of the demand side technology, considering flexible electric heating systems, is integrated in a traditional unit commitment model. Then, in a methodological case study, the results from the proposed integrated model are compared to those from models with focus on the supply side or on the demand side. In that way, we show the advantages and disadvantages of the integrated modeling approach. Results show that neither a price-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 considering a fixed price profile 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. These results indicate that the effect of the elastic demand on the electricity price must be take into account when scheduling e.g. thermal loads under ADR schemes. Integrated models take into account all the above mentioned effects, but are difficult to set up due to the needed detail and are computationally expensive to solve. Merit order (MO) models for the electric power system, combined with a detailed demand side model, are capable of approximating the results of the integrated system model, but are significantly faster to solve. Based on these results, we formulate some conclusions for modelers to select the modeling approach suited for their problem, weighing the detail enclosed in the model formulation and computational efforts.

The remainder of the paper is organized as follows. Before moving to the integrated model developed for this paper and the corresponding results, we present a brief literature review on ADR modeling approaches. We focus on the literature in which thermostatically controlled loads are subjected to ADR measures. In Section 3 we present the integrated model developed for this paper and the methodological case study for which we obtain our results. Results are first presented for the integrated model (Section 4.1) in order to facilitate the interpretation of the shortcomings of other models. Subsequently, the challenges in modeling ADR via price-elasticity models and virtual generator models for the demand side or price profile and merit order models for the supply side are illustrated. Based on these results, we formulate some general conclusions for the use of these modeling approaches (Section 4.6). In each application, the integrated model remains the reference model, used to validate other approaches.

2. Literature review

As mentioned before, different modeling techniques for studying the effects of price-responsive or flexible users are used in the literature. Thus, in order to show main characteristics and performance of the existing operational tools, a review of the state-of-the-art models is presented showing models with a focus on the supply side (Section 2.1), models with a focus on the demand side (Section 2.2) and models with an integrated approach, taking into account the physical behavior of demand side technologies together with the techno-economic characteristics of the electric power system (Section 2.3).

2.1. Models with focus on the supply side

To study electric 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. As indicated above, two main representations of the flexible demand side can be identified: price-elasticities and so-called virtual generator models (VGM).

The price-elasticity is a measure of the change in demand in response to a change in the price of electricity. The assumed range of elasticities used in these models typically stem from analyses of historical data [14, 37], sometimes combined with a simulation model [38]. Among others, De Jonghe et al. [13, 14] developed an elasticity-based operational and investment model to determine the optimal generation mix. Sioshansi and Short [15] employed an elasticity-based model, comparable to that proposed in [14], to study the effect of real-time pricing on the usage of wind power. Kirschen and Strbac [16] proposed a general scheme to incorporate the short-term elasticity in generation scheduling and price setting. Bompard et al. [17] studied the effect of demand elasticity on congestion and market clearing prices via a linear price-elasticity model combined with an optimal power flow formulation.

Virtual generator models are typically used when a modeler wants to include the technical limitations of the demand side technology. The demand is modeled as an electricity generating or storage unit with a negative output. Demand reductions and shifts can be constrained in e.g. amount, time and ramping rate. Energy storage and possible losses can be incorporated (e.g. via a demand recovery ratio; see Section 4.3). The constraints can be based on observations or detailed physical models. The VGM is dispatched similarly as a conventional power plant and therefore often used in the setting of direct load control [14]. These VGM have been used in various studies, e.g. to investigate the impact of ADR on the marginal benefit for consumers [18], the effect of ADR on reserve markets [19], the impact of ADR in electric power systems with large wind power penetrations [20] and the benefits of demand side participation in the provision of ancillary services [21].

However, in both cases a modeler cannot assess the benefit of the studied ADR scheme for the consumer based on these aggregated representations. Moreover, the feasibility of the resulting demand can be questioned, as one has no guarantee that the resulting electric power demand profile will be sufficient to ensure the required thermal comfort for the end-consumer.

2.2. Models with focus on the demand side

Kosek et al. [39] give an overview of the possibilities of implementing ADR. The approach taken in that paper is that of predictive and direct load control. Assuming perfect predictions and no model mismatch, this is the best case scenario for ADR, and hence ideal for impact studies. Thermal energy storage as an ADR technology is often investigated in the literature as a demand side technology. E.g., Hewitt [40] 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 and, in order to assess the benefits for the consumers and generators under ADR, he highlighted the necessity of taking 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 [22–27] to determine the electrical load pattern modification. 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.

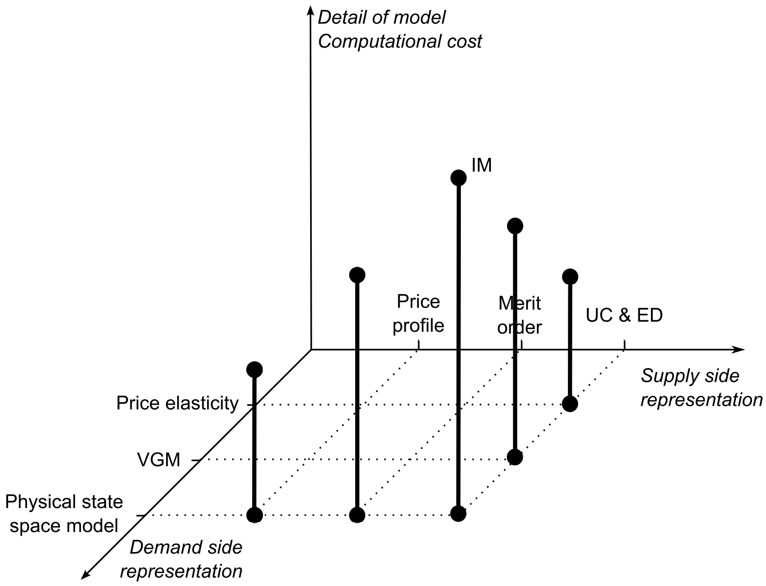


Figure 2: Schematic representation of the various modeling options, in order of ascending complexity and detail, in demand and supply side representations, and the combinations discussed in this paper.

Based on such models, one can only draw conclusions for a single, small consumer. As of a certain number of consumers participating in the studied ADR program, their modified behavior would start affecting the price. This feedback of user behavior on the price of electricity is not taken into account in these models.

2.3. Integrated operational models

Recently, a number of authors have developed integrated models. Both the demand side and the 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 [28–33], inspired by the model of Callaway [34],closely related to the objective of this work. They studied comfort-constrained distributed heat pump management and intelligent charging of electric vehicles (1) as balancing services, with a particular focus on balancing wind power, (2) as a spinning reserve resource and (3) as a voltage stabilizing measure. The physical models of the heat pumps and electric vehicles are integrated in a linear programming representation of the electric power system. Hedegaard et al. [11, 35] developed an integrated model, including different types of TES and emission systems, to assess the potential of ADR to balance wind power. However, some aspects of the thermal system were represented too simplistically in the model. E.g., the heat pump COP (coefficient of performance) is not temperature dependent and the solar transmission through the windows is not taken into account. Dallinger and Wietschel [41] assessed the electric vehicles potential for balancing the fluctuations of renewable energy sources (RES), while representing the generation side by a MO model.

Those integrated models incorporate in some way both the dynamic behavior of the supply side of the electric power system and the flexible electricity demand (represented by electric heating systems for the purposes of this study)[3]. Such an approach offers a number of advantages when a sufficiently detailed representation of the overall energy system is used. First, the electricity demand from the thermal systems is closer to reality, since the occupants behavior is taken into account, as well as the weather conditions and the thermal behavior of the considered heating systems and dwellings. Second, all feedback effects of the redistribution of the electrical load - on demand and supply side - are represented correctly. For example, the losses (electrical and thermal) associated with load shifting can be precisely determined. Third, it allows

[3]Note that the difference between a VGM-like model and an integrated model is not strictly defined, but depends on the level of detail of the demand side representation required by the demand side technology at hand.

identifying the technology that was used to perform the electric load shifting, thus comparing the impact of multiple flexible demand side technologies. Last, it ensures the end-use functionality of the demand side technology, while simultaneously guaranteeing the availability of the balancing services provided by ADR on the supply side. However, those models are not devoid of disadvantages. First, the representation of e.g. a realistic building stock and the stochastic behavior of the occupants requires a detailed demand side model, which is difficult to set up and calibrate. Second, these models are typically difficult to solve numerically, with a high computational cost as a consequence.

The reference model presented in this paper belongs to that category of integrated optimization models. However, in terms of modeling, it improves the approach by Williams et al. [28] by incorporating a more detailed representation of the demand side (occupant behavior, demand side technologies and thermal behavior of the dwellings) and by expanding the linear programming model of the electric power system to a more realistic mixed integer linear programming model. The latter allows to incorporate start-up and shut-down costs and certain techno-economical constraints with regard to on- and off-times of electric power plants, while the former allows to incorporate solar and internal gains, which form a non-negligible part of the thermal power supplied to the dwellings as shown later.

3. Methodology

In this section, we first present an integrated operational model of a typical electric power system and a variable electricity demand from buildings using electric heating systems, composed of heat pumps and auxiliary electric resistance heaters. These heating systems provide both domestic hot water (DHW) and space heating (SH) via radiators. Thermal energy storage – allowing the model to shift demand for electric power in time – is provided via the hot water storage tank and the thermal mass of the building. As will be shown later, the model minimizes the total operational cost for simultaneously (1) satisfying a certain fixed demand for electric power and (2) providing a certain degree of thermal comfort for the occupants of the modeled dwellings.

Afterwards, with the aim of showing the importance of integrated tools for representing ADR, a comparison among several models with a different level of complexity is presented. Fig. 2 shows schematically how the model detail and computational cost depend on the complexity of the supply side model and the demand side model. The analysis is performed starting from the integrated model, representing in detail both the supply side and the demand side, and then reducing step by step the complexity of the supply and the demand side representations respectively. The integrated model represents the supply side by means of a unit commitment and economic dispatch model and the demand side by means of a physical state space model of the building and its heating system. Moving along the reduced complexity of the demand side, the latter can be represented by a VGM or by a price elasticity based model, while the supply side is still represented via the unit commitment and economic dispatch model. Vice versa going toward a simplification of the supply side model, a MO model or an electricity price profile can simulate the supply side of the electric power system, keeping the physical state space model for the flexible demand. In every case the resulting model is used in an optimization problem, with the purpose of minimizing the overall operational costs. The models mentioned above were selected because they are widely used in the literature. Note however that other models and combinations of models may exist. To facilitate the interpretation of the presented discussion, the results obtained for a methodological case study with the IM are presented first as reference in Section 4.1. Second, it was checked whether the simplified models could reproduce the same behavior of the overall system and whether the necessary inputs were available to the modeler. These results can be found in Sections 4.2 to 4.5.

The proposed integrated model for the demand side and the supply side

The integrated model is used in an optimization problem, in which the overall operational cost of the electricity generation is minimized, subject to techno-economic and comfort constraints of both the supply side and the demand side of the electric power system. This mixed integer linear programming (MILP) model combines a unit commitment and economic dispatch model on the supply side with a detailed representation of the physical (thermal and electrical) behavior of the dwellings and their electric heating systems. The model is implemented in GAMS 23.7 and MATLAB 2011b, using the MATLAB–GAMS coupling as described by Ferris [42]. CPLEX 12.5 is used as solver. A full description of this model and the data used is available online [43].

Via the UC and ED model, the commitment status (binary variable z, the on/off status of the power plant) and the hourly output of each power plant (g) 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, $c(g, z)$, consists of fuel costs (FC), emission costs (CO_2T), ramping costs (RC) and start-up (SC) costs:

$$min \quad c(g,z) = \sum_i \sum_j SC_{i,j} + FC_{i,j} + RC_{i,j} + CO_2T_{i,j} \tag{1}$$

where i represents the power plant and j the time step, equal to one hour in this study. The fuel costs and carbon emission costs depend on the output and the (part-load) efficiency of the power plant. Start-up costs are due whenever a power plant starts up, while ramping costs reflect the degradation of the plant due to changes in output.

In the integrated model, the demand for electricity that needs to be met consists of two parts: a fixed electricity demand profile (d_j^{fix}) and the electricity demand from the flexible demand side technology (d_j^{var}), characterized by a certain market penetration, mp. In this integrated model, it has been assumed that demand and supply are controlled centrally (direct load control). The demand for electricity at each time step j needs to be met by generation of electric power by conventional power plants i (g_{ij}) plus the electric power generated from RES (g_j^{RES}):

$$\forall j: \quad d_{\mathrm{j}}^{\mathrm{fix}} + mp \cdot d_{\mathrm{j}}^{\mathrm{var}} = \textstyle\sum_i g_{i,j} + cur_j \cdot g_j^{RES} \tag{2}$$

$$\forall j: \quad 0 \leq cur_j \leq 1 \tag{3}$$

In this equation the decision variable cur_j stands for the relative curtailment of RES-based electricity generation and has a value that varies between 0 (full curtailment) and 1 (no curtailment). Curtailment costs are assumed to be internal transfers within the model and are thus not explicitly modeled. The only net cost perceived by the system is the opportunity cost of not using the zero-cost RES power available. Likewise, the redistribution of the operational costs and benefits of ADR among producers and consumers occurs internally and is thus not modeled explicitly. The fixed demand and RES-based electricity production profiles used are based on hourly demand data for Belgium for 2010 [44]. The variable electricity demand, instead, is a decision variable, determined by the comfort constraints of the occupants of the considered dwellings, calculated via the demand side model. This demand side model describes the physical behavior of the electric heating systems, which deliver heat for domestic hot water production and space heating by means of a heat pump and an auxiliary electric heater. The thermal behavior of the house, radiator and domestic hot water storage tank is modeled through a linear state space model, that allows converting the thermal comfort demand in a demand for thermal power for each dwelling, which needs to be satisfied by the electric heating systems. The state space model that describes the thermal behavior of the building and its heat emission system can be summarized as

$$\forall s,j: \quad T_{s,j+1}^{\mathrm{SH}} = A \cdot T_{s,j}^{\mathrm{SH}} + B \cdot U_{s,j}^{\mathrm{SH}} \tag{4}$$

The symbol $T_{s,j}^{\mathrm{SH}}$ stands for five states considered in this model, consisting of the indoor operative temperature, along with temperatures representing the thermal behavior of the inner and outer walls, the roof and the floor slab. Likewise, we have retained five inputs $U_{s,j}^{\mathrm{SH}}$: the ambient air and ground temperature, the solar and internal heat gains and the heating input of the radiators. The state space matrices A and B make up a linear model describing the thermal conductances and capacities in the system, along with linear approximations of the convective and radiative heat transfer coefficients. As thermal comfort must be achieved, the temperatures in the heated zones are constrained to temperatures that are perceived as comfortable. If the occupants are present in residence s at time step j, the temperature in the heated zone ($T^z_{s,j}$) should neither exceed T^{max}, nor fall below T^{min}_p (occupants present and awake, $occ_{s,j}$=1) or T^{min}_{np} (occupants absent or sleeping, $occ_{s,j}$=0):

$$\forall s, j: \quad T^{\min}_{\mathrm{p}} \cdot occ_{\mathrm{s,j}} + T^{\min}_{\mathrm{np}} \cdot (1 - occ_{\mathrm{s,j}}) \leq T^{\mathrm{z}}_{\mathrm{s,j}} \leq T^{\max} \tag{5}$$

These constraints will impose limits on the thermal inputs of the building $U^{\mathrm{SH}}_{s,j}$, and hence on the electric power consumed by the heating systems. As the electricity demand of each residence is the sum of the electricity demand of the heat pump (P^{HP}_j) and the auxiliary heaters (P^{AUX1}_j, P^{AUX2}_j), the total variable electricity demand ($P^{el}_{j,s}$) in residence s on time step j and the total variable demand on system level $d^{\mathrm{var}}_{\mathrm{j}}$ become:

$$\forall j: \quad d^{\mathrm{var}}_{\mathrm{j}} = \sum_{\mathrm{s}} P^{\mathrm{el}}_{\mathrm{j,s}} = \sum_{\mathrm{s}} \left(P^{\mathrm{HP}}_{\mathrm{s,j}} + P^{\mathrm{AUX1}}_{\mathrm{s,j}} + P^{\mathrm{AUX2}}_{\mathrm{s,j}} \right) \tag{6}$$

Both the supply side and demand side models were validated separately which proved the accuracy of their results [45–49] , thus it is reasonable to assume the same reliability for their coupling. In particular, the model structure of the demand side model is very similar to that proposed by Širokỳ et al. [46], Oldewurtel et al. [47] and Henze et al. [48]. The accuracy of the heating system model is tested against a detailed physical simulation model using the IDEAS library [50] in Modelica, as described in [49].

The performance of this integrated model will be studied in a methodological case study. The supply side of the electric power system considered consists of 1 nuclear power plant (1200 MW), 5 coal-fired steam power plants (4000 MW), 10 gas-fired combined cycle power plants (CCGT, 4000 MW) and 10 peaking units (open cycle gas turbines and oil-fired power plants, 1000 MW). We assume that RES-based electrical energy accounts for 20% of the generated electrical energy over the simulated period (48 hours, see below). A carbon price of 30 $\frac{EUR}{ton\ CO_2}$ is assumed. Note that this high carbon price increases the variable cost of coal-based generation above that of gas-based generation with CCGTs. Twenty five identical buildings, with a different user behavior and number of users based on the demographic structure of Belgium [51], are considered. Their demand is summed and scaled on the basis of the market penetration (mp) to represent the total variable electricity demand profile. Unless otherwise specified, the electric heating systems consume 25% of the total electrical energy produced over the simulated period. The fixed demand profile is scaled (1) to represent a certain fraction of the total demand for electrical energy on the considered optimization horizon and (2) to ensure that the peak demand does not exceed 90% of the installed conventional capacity. The parameters for the building model were derived by Reynders et al. [52] by performing model reduction on a detailed model of a typical Belgian building built between 2005 and 2010. The building considered has a floor surface of 270 m^2 and a protected volume of 741 m^3. Infiltration and ventilation combined cause 1.5 air changes per hour. The exterior walls, roof and windows respectively have a U-value of $0.4\frac{W}{m^2K}$, $0.5\frac{W}{m^2K}$ and $1.4\frac{W}{m^2K}$. The building has an average of about 10 m^2 of window surface in each cardinal direction. Flexibility is available via thermal energy storage in the building shell and the hot water storage tank. The constraints on the thermal comfort required by the occupants (e.g. temperature constraints [53] and the availability of hot water [54]) result in constraints on the electrical power demand and on the flexibility offered to the supply side. 48 hours of a typical winter period are retained in the evaluation in order to limit the calculation time. This period is sufficient to illustrate the advantages and disadvantages of the various models. Cyclic boundary conditions are enforced on the optimization.

All alternative models, as discussed in Section 2.1 and 2.2, are simplifications of the presented integrated model. For example, the use of a virtual generator model to represent the demand side flexibility would abolish the need for the linear state-space model, while leaving the supply side model unaffected. The linear state-space model could be replaced by a (simpler) generic model of a storage unit, with some constraints that ensure that sufficient electric power is 'consumed' to guarantee thermal comfort. Likewise, reducing the supply side model to a merit order model would strongly simplify the unit commitment model, while leaving the linear state-space model at the demand side unchanged. In the subsequent section we will further detail these simplified models where needed.

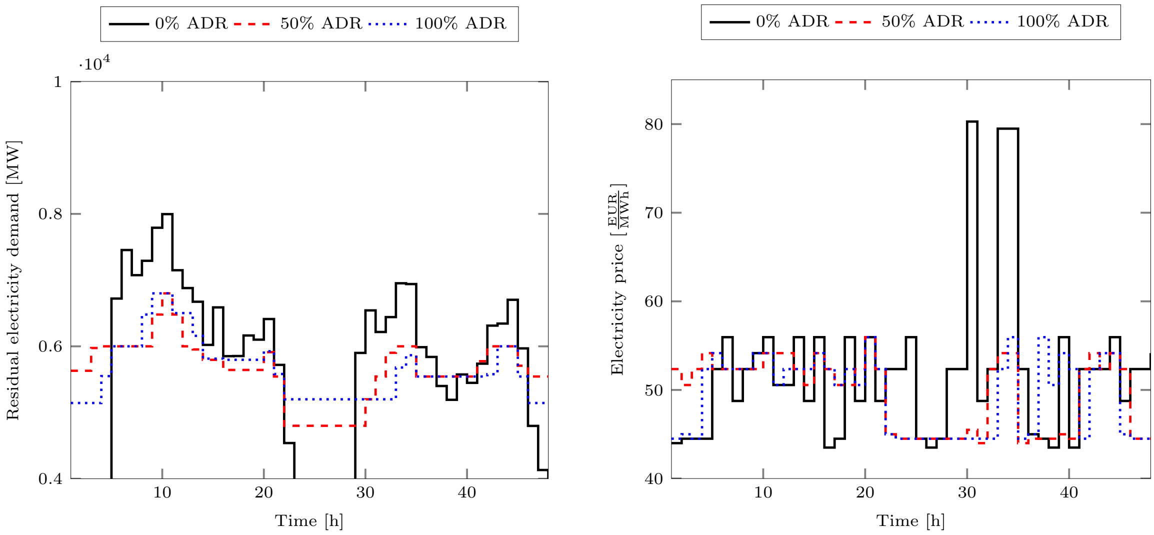
4. Results and discussion

In this section, we will show that (1) the price-elasticity of storage-type customers is difficult to estimate ex-ante, limiting the usability of price-elasticity-based models (Section 4.2); (2) thermal energy storage losses, which are typically non-linearly dependent on e.g. the state of charge, are difficult to capture in VGM-like models (Section 4.3) (3) price profile-representations of the electric power supply neglect the possible effect a changed demand profile may have on the electricity price (Section 4.4) and (4) merit order models, in combination with a physical model of the demand side, allow to approximate the operational performance of the integrated model at a reasonable computational cost (Section 4.5). To facilitate the interpretation of these results, the starting point of the presented analysis will be the results obtained with the integrated model (Section 4.1). The integrated model (IM) is the most detailed in both supply (unit commitment and economic dispatch) and demand (physical models of buildings and heating systems) and will act as a reference. To conclude this section, we discuss the most important results and differences between the various models in Section 4.6.

4.1. Integrated model results

As pointed out previously, the interaction between the supply side and demand side (models) can be observed in the mutual changes in the residual electricity demand and the electricity price profile (as will be recalled from Fig. 1). Fig. 3a shows the residual electricity demand obtained from the integrated model, calculated as the total electricity demand minus the RES-based generation. The controllable demand from the electric heating systems was assumed to participate to the ADR program fully (100% ADR), partly (50%) or not at all (0% ADR). In the last two cases, (part of) the consumers (is) are not exposed to the hour-to-hour variations of the electricity price. This triggers the minimum electrical energy use at the demand side: each consumer minimizes his own energy cost by minimizing his energy use. When the customers adhere to the ADR program, the demand is shifted to the hours of lower consumption, hence lower electricity costs, and so-called ‘valley filling’ occurs. Load shifting however leads to additional thermal losses, hence an increased overall energy use.

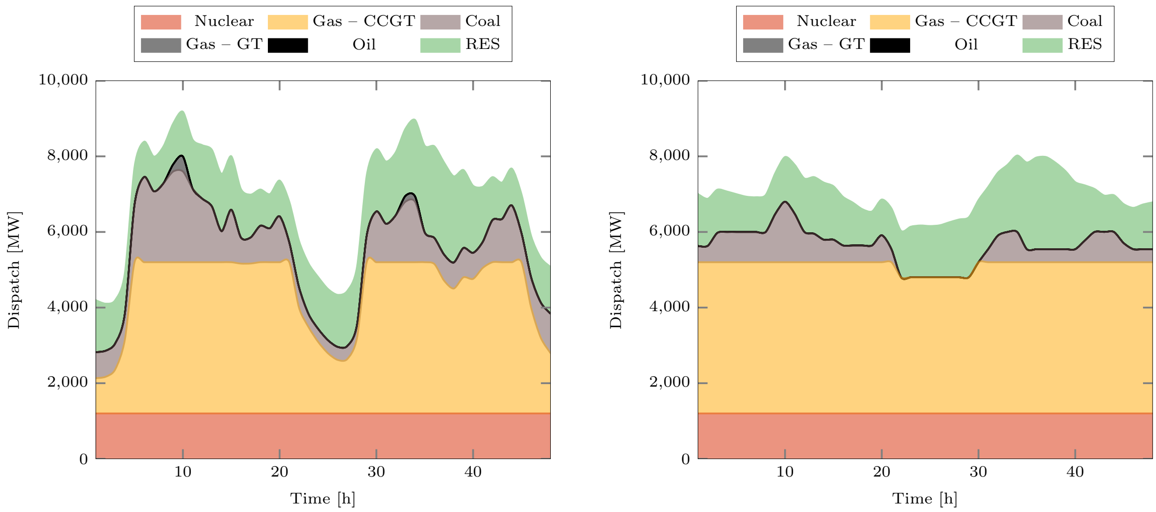
Fig. 3b shows the electricity price profile obtained from the IM. For the minimum energy demand scenario (0% ADR), the price shows some peaks, corresponding to the peaks in demand, which leads to the activation of expensive peaking units (Fig. 4). Increasing the participation of the electric heating systems to the ADR program flattens the price profile. The difference between the case with no participation to the ADR (0% ADR) and the case with a partial participation to the program (50% ADR) is very evident, while the difference is less pronounced between the latter and the case with total participation to ADR (100% ADR). This illustrates that after a certain threshold the marginal effect of ADR on the production side is reduced. These observations are confirmed by the corresponding dispatch, shown in Fig. 4, and the residual electricity demand profile, Fig. 3. Moving from a 0% ADR participation to a 50% ADR participation, the need for expensive peaking units disappears completely due to the flattened demand. The same units, being the combined cycle gas turbines, set the price throughout the optimization period. As such, large price differences between hours – the driving force behind the demand redistribution under ADR programs – disappear. Therefore, additional controllable heating systems will not result in significant changes in demand, nor electricity prices, on the level of the power system. Note however that, to obtain the same flexibility on a system level, each individual consumer needs to shift his demand less and the resulting thermal losses, thus additional consumption, per consumer will be lower (see further).



(a) Residual demand

(b) Electricity price

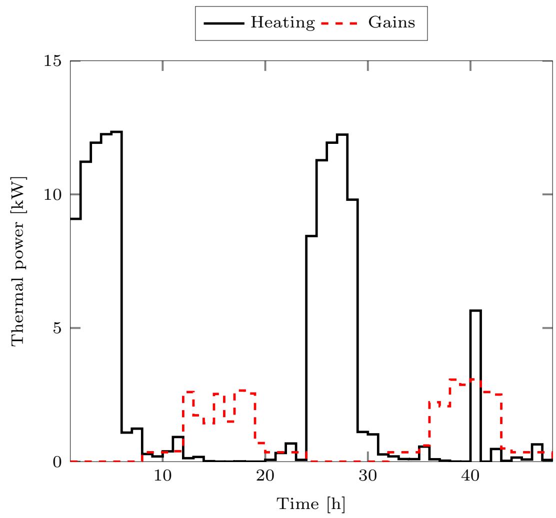
Figure 3: The residual electricity demand (left) and electricity price (right) in three cases of ADR participation (0%, 50%, 100%). RES-based generation is assumed to cover 20% of total demand for electrical energy.



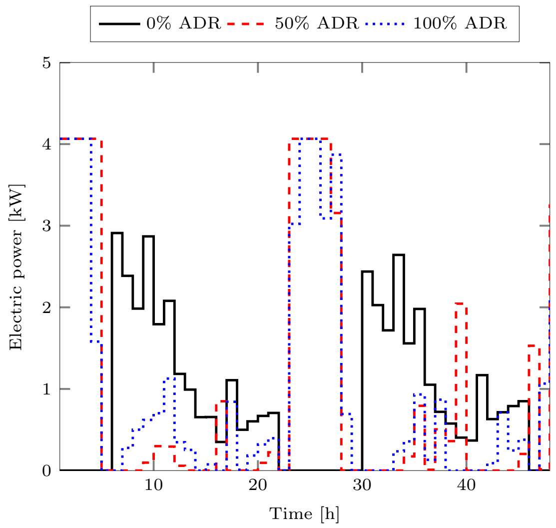
(a) No ADR participation

(b) 50 % ADR participation

Figure 4: Output of the committed power plants in case of 0% (left) and 50% (right) ADR participation. RES cover 20% of the electrical energy demand, while electric heating systems account for 25% of the total electrical energy demand.

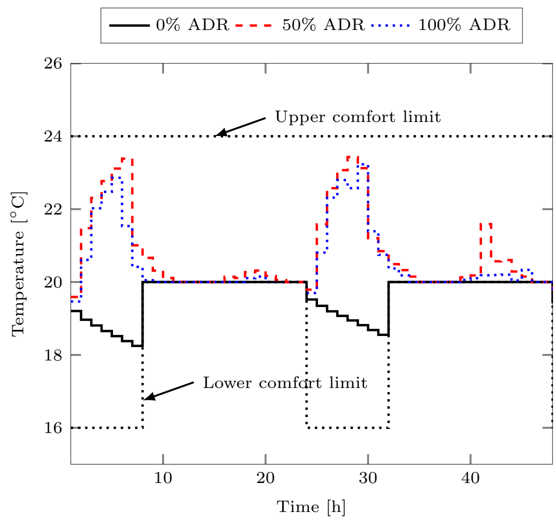


(a) Breakdown of the thermal power supplied to a building in power supplied by the heating system and the gains (internal and solar gains). The 'heating power' profile was obtained from the optimization with a 50% ADR participation (red, dashed line in Fig. 5b).

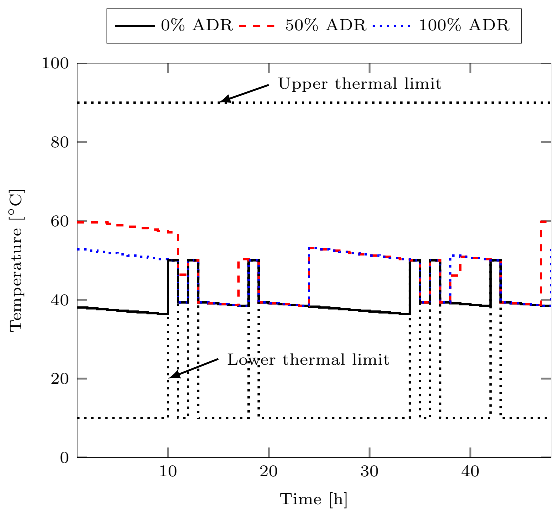


(b) Electricity demand of the heating system of a single building in three different cases of ADR participation (0%, 50%, 100%) for a single building.

Figure 5: The thermal and electrical power supplied to one of the dwellings on the two simulated days under different ADR participation scenarios (0%, 50%, 100%).



(a) Indoor air temperature



(b) Domestic hot water tank temperature

Figure 6: Building indoor temperature (Fig. 6a) and DHW temperature (Fig. 6b) over the two simulated days under different ADR participation scenarios (0%, 50%, 100%).

As to the demand side, Fig. 5a shows the trend of the demand for space heating and domestic hot water of a building and its breakdown in the principal contributions, being the thermal power provided by the electric heating system ('heating' in Fig. 5a) and the internal and solar gains due to the interaction of the building with users and surrounding ('gains' in Fig.5a). Fig. 5a shows that the contribution of the internal and solar gains, especially in the afternoon hours of the day, represents an important share of the thermal energy demand, reducing the thermal energy to be provided by the heating system. It is therefore relevant to take these gains into account and neglecting them would lead to a considerable error in assessing the thermal load of the heating system. Moreover, these gains are dependent on the outside temperature and solar irradiation, as well as on the user behavior.

Fig. 5b instead shows the electricity consumption pattern of the heating system of a single building in different ADR cases. With ADR, the overall operational system costs are minimized by exploiting the flexibility of the electric power demand of the heating systems, due to the storage capability of the thermal loads, both in the building envelope and in the DHW storage tank. Due to the availability of cheap generation capacity during the night, the building is preheated compared to the case of no ADR participation (0% ADR) (Fig. 5b). In fact, the electricity consumption is shifted to low price periods and the energy is stored in the thermal mass of the building (Fig. 6a) or in the storage tank (Fig. 6b). This causes more thermal losses and hence a higher energy use, though the overall operational system cost is lower. As a consequence, the inside temperature of whatever ADR case, even if the thermal comfort is maintained, can be higher than the minimum energy case, in which the temperature is as low as possible while maintaining thermal comfort (Fig. 6).

The importance of a correct representation of the thermal losses at the demand side technology is illustrated by the demand recovery ratio (DRR). The DRR is defined as the ratio between the observed electrical energy used by the flexible electric heating systems and the minimum electrical energy use of those heating systems [14, 36]. DRR is therefore always greater than or equal to 100%. Results obtained with the integrated model indicate that the DRR behaves erratic with respect to the share of variable demand and renewable energy in the system. At a 50% ADR participation, it varies between 105% and 109%, while this range reduces to 102 to 105% at a 100% ADR participation rate. The DRR is lower for a 100% ADR participation, since less load shifting per house is necessary when more customers are involved. Thus, the behavior 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 behavior of the other consumers.

Although the presented results highlight many advantages of the integrated modeling approach, it is not devoid of disadvantages. The most serious concern is the computational cost of solving such an integrated model. In this particular setting, solving the integrated model for 48 hours takes about 30 minutes on a 2.8 GHz quad-core machine with 4 GB of RAM. Therefore, modelers often resort to simplified models on the supply or demand side. This will be discussed below.

4.2. Unit commitment models with a price elasticity model on the demand side

As outlined in Section 2.1, many studies on demand side flexibility use a price elasticity model to describe the price responsiveness of flexible customers. This elasticity is defined as

$$\epsilon_{\mathrm{u,k}} = \frac{\partial d_{\mathrm{u}}}{\partial p_{\mathrm{k}}} \cdot \frac{p_{0,\mathrm{k}}}{d_{0,\mathrm{u}}} \tag{7}$$

with p_{k} the price of electrical energy in hour k, and d_{u} the demand for electrical energy in hour u. The index 0 indicates the initial or anchor electricity demand and price levels, i.e. the reference demand and price levels to which the elasticity will be related. 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. For example, as shown above, the redistribution of demand may yield a higher overall electricity consumption, which 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 may not be suited to describe the responsiveness of storage type customers when storage is accompanied by losses not linearly dependent on the energy stored or on the power supplied, such as thermal systems.

When a modeler seeks to use price-elasticities to model the behavior of price-responsive consumers, he needs to estimate these elasticities ex-ante. I.e., the modeler needs to assume a certain (range of) price-elasticity values before observing the reaction of the price-responsive customers. However, this is not a

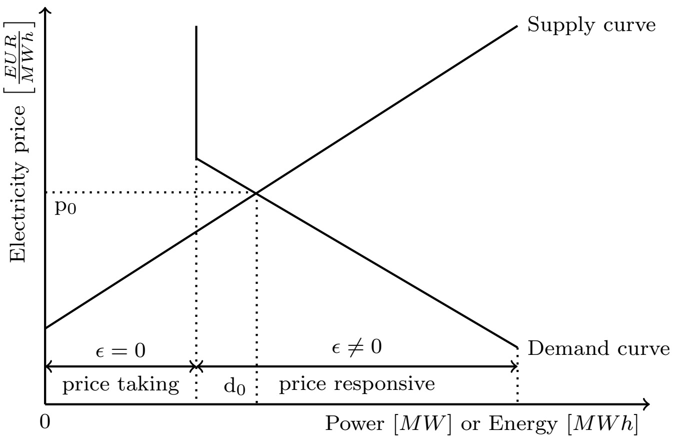


Figure 7: Schematic representation of the partly elastic, partly inelastic demand, simulated in this paper. The intersection of the demand and supply curves yields the anchor points (p_0, d_0) for the elasticity calculation [18].

trivial task for new types of consumers, such as electric heating systems. Moreover, one might observe behavior that cannot be captured via a linear relationship between price and demand. To illustrate this, we used the integrated model to assess the mutual change of price and demand induced by the modification of the RES profile. This is equivalent to shifting the supply curve along the demand axis (Fig. 7 and 8). 180 RES profiles were considered (wind power profiles, obtained from the Belgian TSO, Elia, for the year 2013). Each of these profiles covers 20% of the demand. Due to a change in the RES profile, the consumers will see different electricity price levels as the supply curve changes. The thermal heating demand (i.e. the thermal comfort) remains unchanged in these simulations. The electricity reference price as seen by the electric heating systems is here calculated as the marginal value of the market clearing condition (Eq. (2)) in the integrated model (Fig. 7).

From these simulations, one can obtain the price-demand couples for each of the respective hours. Fig. 8 shows the resulting price-demand couples for hour 30, in which the demand for thermal services is significant (Fig. 5b). Similar effects are observed at other time steps. If a price-elasticity could describe the change in demand in response to changes in the cost or price of electricity, the price-demand couples would form a straight, downward sloping line, as schematically illustrated in Fig. 7. However, as shown in Fig. 8, this is not the case. First, one can observe some atypical increases in demand in response to an increase in the marginal cost of electricity generation. This would correspond to a positive own-elasticity, which is uncommon in the electricity sector [14]. Second, different demand levels appear optimal for the same price level. A(n) (own) price-elasticity does not allow capturing these effects. These results show the difficulty of correctly predicting the elasticity ex-ante, needed to study ADR via an elasticity-based model, when storage-type customers are involved.

4.3. Unit commitment models with virtual generator models on the demand side

A flexible demand can be modeled through a virtual generator model (see Section 2.1). In essence, the demand is described as a generating or storage unit with a negative output and a set of constraints on this output. A generic description of any storage unit can be formulated as follows:

$$E_t = E_{t-1} - \dot{L}_t \cdot \Delta t - \dot{D}_t \cdot \Delta t + \dot{I}_t \cdot \Delta t + \dot{G}_t \cdot \Delta t \tag{8}$$

The state of charge of any storage system at a certain time step t (E_t), is typically modeled based on the energy content at the previous time step $t-1$ (E_{t-1}), and the withdrawal and the addition of energy during that time step t. In this equation, E_t stands for the energy content of the virtual storage unit, Δt for the considered time step, $\dot{L}_t$ for the (thermal) losses of this unit, $\dot{D}_t \cdot \Delta t$ for the energy demand (i.e. the amount of energy one extracts from the storage, the output), $\dot{I}_t$ for the power supplied to the storage and $\dot{G}_t$ for any

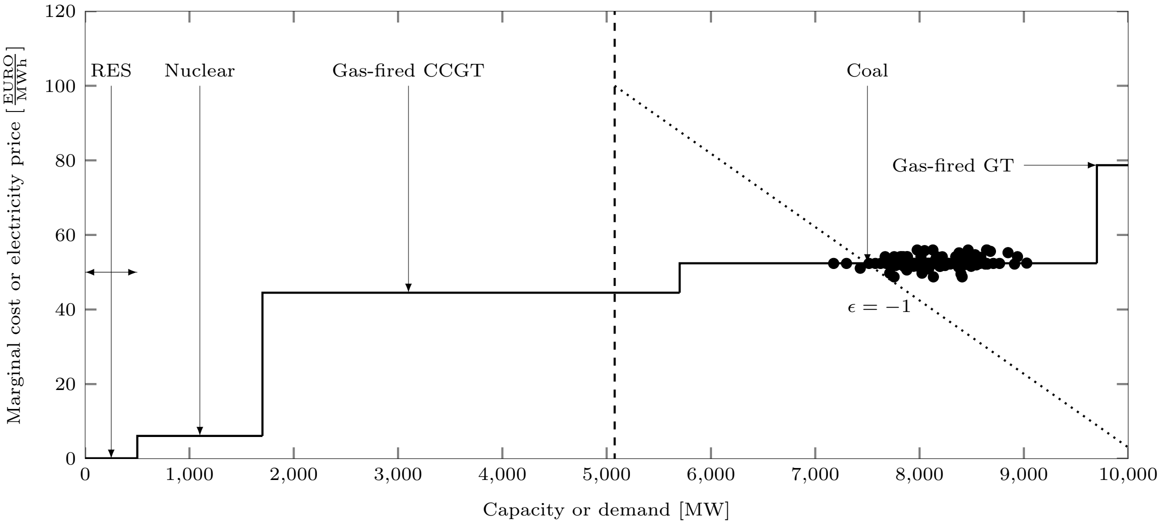


Figure 8: The resulting price-demand couples in hour 30, indicated by the black dots in the figure above, indicate that the price-responsiveness of thermal systems cannot be captured via an own-price elasticity. The solid line shows the supply curve, the dashed line indicates the inelastic part of the demand. The supply curve shown above is a simplified merit order-representation of the supply side of the electric power system. For illustrative purposes, the dotted line shows a demand curve characterized by an own elasticity of -1. The RES-based generation in hour 30 varies between 346 and 4,099 MW.

other gains. Constraints on each term in Eq. (8) can be imposed to ensure that the technical constraints of the demand side technology and the comfort constraints of the consumers are respected. Again, the constraints and interaction terms, such as the loss term L, must be quantified by the modeler ex-ante.

When this modeling approach is used to simulate a flexible storage type customer with electric heating system as demand side technology, the limits on the output of the virtual generating unit (electrical power demand) can easily be deducted 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 (heat pumps) can ramp up and down well within the time step (1 hour). A similar reasoning applies to the limits of on and off-times. Constraints are also required on the size of the 'storage' unit, which typically consist of minimum and maximum energy limits for the storage capacity combined with a loss term (or efficiency, L). The thermal losses, L, and the gains, G, in Eq. (8) capture the interaction of such a thermal system with its surroundings. These parameters, which can usually be easily quantified for some flexible loads such as electric vehicles, become rapidly more complex to estimate for thermal energy storage systems. Indeed, the thermal losses and gains are not only temperature and time dependent, but they are also dependent on user behavior (consumption of hot water, occupancy profiles), weather conditions (ambient air temperature, solar heat gains) and the building structure (wall thickness, ventilation rate [10]) . The importance of solar and internal heat gains has been highlighted previously in Section 4.1 (Fig. 5a), where it has been shown that they represent a considerable share of the building thermal demand. Neglecting to model these gains would yield a significantly lower state of charge, which in turn may result in an overestimation of the electricity demand via a VGM. Thus, in reality, this may lead to a violation of the comfort constraints on the consumers side. In addition, the DRR, which by its definition can be interpreted as a measure for the loss term L, shows an erratic behavior with varying the RES and ADR share, that is clearly difficult to be estimated ex-ante. Likewise, time-dependent limits on the state of charge of the storage system could be used to represent the thermal comfort requirements of the occupants. Similar to the thermal losses and gains, these limits are highly dependent on the user behavior and weather conditions. In conclusion, the representation of a demand side thermal energy storage system and its interaction with the supply side of the electric power system requires detailed knowledge of the temperatures and disturbances imposed on that storage system. In a VGM it is necessary to estimate these interactions ex-ante, which can affect the reliability of the results.

4.4. State-space models with a price profile-model on the supply side

A price profile is often considered as a possible way of representing the electricity wholesale market in an ADR model focused on demand responsive consumers. Typically a fixed electricity price profile is assumed to represent the supply side, while a detailed physically based model is used for the demand side in order to determine the electricity demand profile that yields the minimum energy cost for the customer. This approach however fails to identify the feedback or reaction of the supply side of the electric power system to a change in the demand side behavior. In fact, 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.

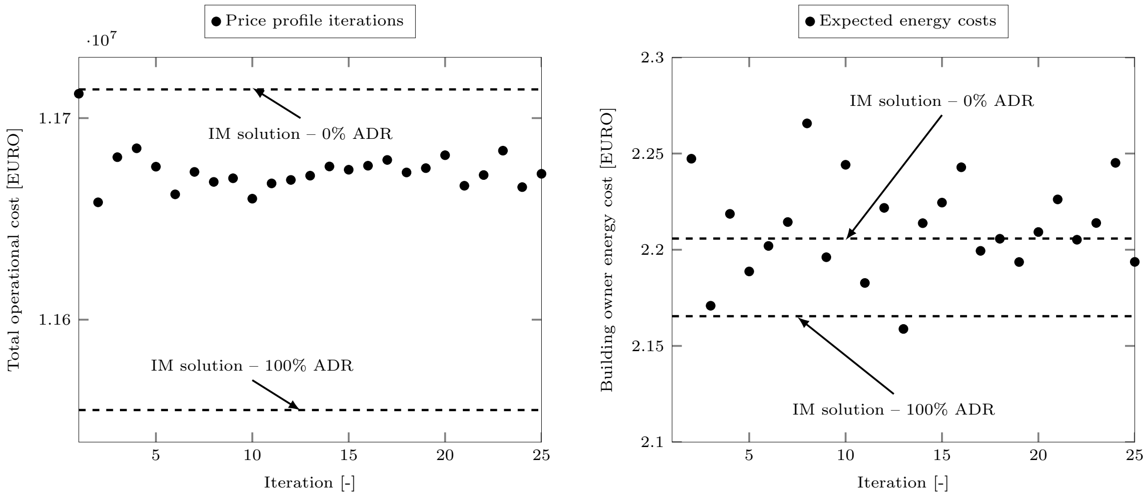
Since in the reference case presented above, the flexible electricity demand has a market penetration assumed to be 25% of the total electricity demand, it is likely that changes in the demand profile of these electric heating systems have an impact on the electricity price. Neglecting this interaction between demand and supply side may have a severe effect on the validity of the obtained results, as we will show below using the context of the methodological case study. Towards that end, we use the state-space demand side model and the unit commitment supply side model separately, as illustrated in Fig. 1. In a first iteration, the demand side model starts from a flat electricity price profile and determines the electricity demand resulting in minimal total energy cost for the owners. This corresponds to minimizing the energy use on the demand side. The supply side model starts from the fixed electricity demand profile, augmented with the demand profile of the electric heating systems determined by the demand side model in the previous iteration. With this model, we determine unit commitment and dispatch that minimizes the total operational cost for the system. The resulting price profile is then passed on to the demand side model. Iteratively, the demand side model is used to calculate a new electricity demand in response to this new electricity price profile, which then is used as an input for the supply side model.

When this iterative process was performed, it soon diverged. The demand side model tends to overreact to differences in electricity price. This results in large peak demands, which can be higher than the generation capacity, when the price is low. A possible way of fixing this issue is by putting an extra constraint on the possible changes in the resulting electricity demand profile between iterations, e.g. by limiting the changes in the electricity demand in each hour to a certain percentage of the electricity demand profile in the previous iteration. Fig. 9 shows the trajectory of the total operational cost of the electric power system in case of a maximum 10% deviation of the demand profile from the previous iteration. The operational costs shown in Fig. 9 are the total operational costs obtained with the unit commitment model, considering the fixed demand and the demand profile from the electric heating systems as obtained from the demand side model. In the first iteration, the model yields the same result as if the electric heating systems would not adhere to any ADR program. The following iterations show the reaction of the demand side model to a changing electricity price profile. The resulting decrease in operational costs is about one third of the total possible operational cost reduction due to ADR as calculated with the IM (about 1.8% [4], to be compared with the 0.1% optimality gap imposed on the optimization).

However, 25 iterations result in a total calculation time in the same order of magnitude as the integrated model. Similarly, when looking at the costs for the building owners, we note an erratic oscillation of the solution compared to the corresponding solution of the IM. The energy costs for the building owner are calculated as the demand profile of the electric heating systems times the electricity price profile used in the demand side optimization.

In conclusion, these results show that conclusions based on models in which the supply side is represented via a (fixed) price profile are biased if changes in demand affect those electricity price profiles. This interaction can be integrated in such a modeling approach to some extent. However, such an iterative approach

[4]Note that these figures account only for operational costs and were obtained for this particular setting. E.g., investment costs are not taken into account. These numbers should not be interpreted as a comprehensive evaluation of the full possible benefits of ADR.



(a) Total operational cost

(b) Building owner energy cost

Figure 9: Evaluation of the total electricity production cost with the price profile demand model using the iterative procedure. The integrated model (IM) values for ADR 0% and 100% are indicated as reference (dashed lines).

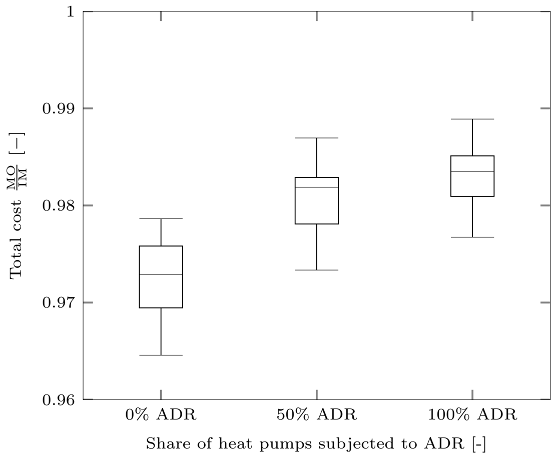
may not yield results of the same quality as an integrated model, but will require the same computational effort. Moreover, the same level of detail is needed in both models.

4.5. State-space models with a merit order model on the supply side

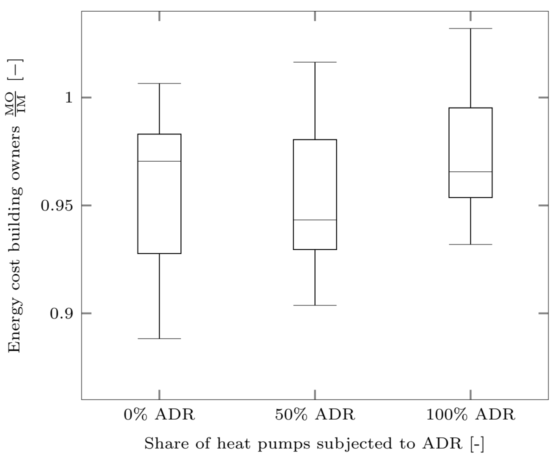
As an alternative to the iterative approach suggested above, a modeler focusing on demand side results could consider a merit order representation of the supply side of the electric power system, in combination with a physical model of the demand side. As explained below, this model allows to take into account the effect of a change in the demand profile on the electricity price profile directly, abolishing the need for iterative procedures. This MO model is computationally less intensive than a unit commitment model. Moreover, it requires far less detail on the supply side and is thus easier to set up.

This simplified model consists of a mere ranking of the different power plants in an ascending order of (average) operational production costs (Fig. 8). These costs consist of fuel and carbon costs. The intersection of the demand and the merit order curve yields the electricity price in each hour. The objective function of this model is similar as in the IM, namely minimize the total operational costs. Furthermore, it couples the demand side model and the merit order model via a (simplified) market clearing condition (Eq. (2)). As such, it is possible to consider the effect of the energy demand variation on the electricity price, even if in a simplified manner. This MO model however only considers the maximum output of each power plant and hence neglects ramping constraints, minimum operating points, minimum on- and off-times and start-up costs, which are considered in a unit commitment model. As a consequence, power plants may be switched on/off in an unrealistic way in the merit order model. E.g., coal power plants are switched on and off within one hour, while in reality it takes multiple hours for such a power plant to start up. Results obtained with such a merit order model should thus always be interpreted with caution, e.g. via a re-evaluation of the resulting demand profile with a UC & ED model as discussed below. Fig. 8 shows the ranking of the different power plants. Fuel costs and CO_2 costs are the same as those assumed for the unit commitment model in Section 3.

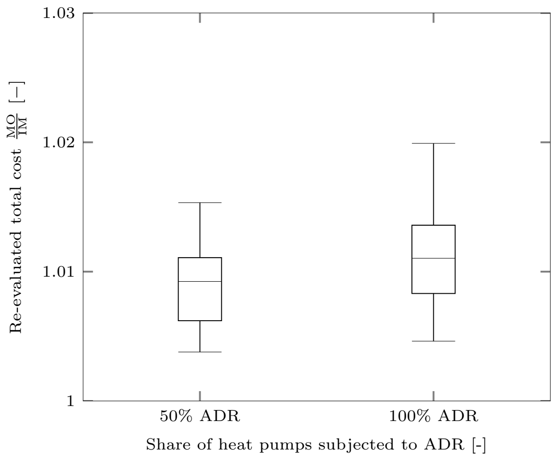
The costs from the MO model have been compared to those from the IM for 18 scenarios for the RES-based generation, namely three different RES profiles that cover 5%, 10%, 15%, 20%, 25%, 30% of the total electricity demand (energy basis) in the considered optimization period. Fig. 10a shows (1) the ratio of the total operational system costs as obtained with the MO model and the IM and (2) the ratio of the energy costs for the building owners as obtained with the MO model compared to the IM. In the upper part of the figure, the costs of the MO model are directly compared to the results of the IM. In the bottom part



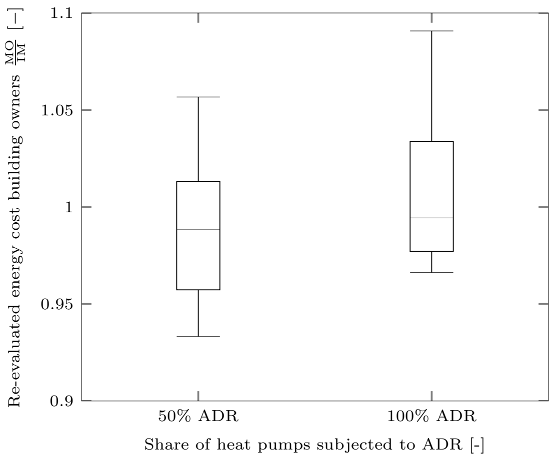
(a) Total operational system cost, as obtained from the MO, compared to the total operational cost obtained with the IM.



(b) Total cost for building owners, as obtained from the MO, compared to the corresponding cost obtained with the IM.



(c) Total operational system cost, re-evaluated with the UC & ED, considering the demand from the electric heating systems as obtained from the MO, compared to the total operational cost obtained directly with the IM.



(d) Total cost for building owners, re-evaluated with the UC & ED, considering the demand from the electric heating systems as obtained from the MO, compared to the corresponding operational cost obtained directly with the IM.

Figure 10: Relative difference in total system costs and building owners costs between the merit order model and the integrated model. The upper figures show the relative difference when considering the costs as obtained directly from the MO. The lower part of the figure contains the same results, but shows the costs after re-evaluation with the unit commitment model. The box plot shows four quartiles in the data, with the middle line being the median of the values.

of the figure, the demand profiles of the electric heating systems, as obtained from the MO, are used as an input of the unit commitment model, in order to recalculate the costs, taking into account all operational constraints and costs of the power plants. With regard to the total operational cost, the merit order model yields a cost between 1 to 3.5% lower than in the case of the integrated model (Fig. 10a). In this case, a modeler thus takes 96.5% to 99% of all operational costs into account when he employs a merit order model. Furthermore, this percentage increases with the share of ADR. ADR has the effect of flattening the residual demand, which makes it less likely that the solution of the MO model violates any dynamic constraint of the power plants. In addition, start-up costs become relatively less important in the IM solution as less start-ups are required. Looking at Fig. 10c, showing the re-evaluated operational cost for the system, one is able to judge the quality of the solution obtained from the MO model. This re-evaluated total operational cost is obtained by solving the UC & ED considering the electricity demand profile as obtained from the merit order-state space model. Total operational costs deviate as little as 0.4% to 2% from the solution obtained with the IM.

Fig 10b and 10d show the energy cost for building owners. The results from the MO model yield cost differences within a range of -12% to +3% compared to the IM solution. After re-evaluation this range changes to -7% to +10%. However, one should be careful in the interpretation of these results. Indeed, the objective of the optimization is to minimize total operational system cost, not the owners cost. The demand profile that yields the minimal operational system cost might not be unique. E.g., a change in the demand profile may lead to a significant difference in the cost for the building owner, but the effect of this change on the total operational cost might fall within the optimality gap of the optimization. From a system perspective, large variations may exist in the owners cost, while system costs remain unaffected.

To conclude, the merit order model successfully takes into account the interaction of electricity prices and the demand profile, especially if one is looking at ADR from a system perspective. Results that are close to those of the integrated model can be obtained, especially after re-evaluation of the solution with the unit commitment model. Solving the MO model takes about 30 seconds, compared to 30 minutes for the IM. Re-evaluating the MO model with the UC & ED model additionally requires 30 seconds.

4.6. Model comparison

The analysis performed above allows us to state the following conclusions from using the different approaches for modeling active demand response when storage-type customers, such as electric heating systems coupled to any form of thermal storage, are involved. We presented an **integrated model**, which employs a unit commitment and economic dispatch model for the supply side of the electric power system and a physical state space model to represent the demand side, as a **benchmark**. This model allows a modeler to correctly asses the effect of ADR on the supply and demand side of an electric power system, but requires a significant computational effort and detailed information to set up the model. It can for example be employed to assess the quality of other modeling techniques.

If a modeler seeks to simplify the demand side model, **price-elasticity** and **virtual generator models** are often encountered in the literature due to their simplicity and low computational cost. However, in the setting of storage-type customers, in both cases it will be very difficult to estimate the models' parameters ex-ante. We have shown that e.g. price-elasticities and demand recovery ratios, as a measure for the losses in a system, fluctuate erratically with the share of ADR and RES in the system. However, the assumptions on the various parameters will drastically affect the obtained results.

Likewise, if the modeler employs simpler models on the supply side, he should proceed cautiously. If one neglects the effect of a change in demand on the electricity price profile, results will only hold for a small group of consumers. Iterative **price profile** approaches will to some extent allow to take into account this feedback and are simple to implement, but results remain sub-optimal and become computationally intensive to solve.

In addition, not taking into account the limitations of the considered power plant portfolio might lead to demand profiles that cannot be met. **Merit order models** consist of a ranking of the power plants according to their operational costs. Although they do not take into account any operational constraints, nor all costs, they allow to approximate the solution of the integrated model in about 1/60th of the calculation time. However, one should take caution in interpreting the results, as the resulting dispatch might violate the constraints of the power plants and not all costs, such as start-up costs are taken into account.

5. Conclusion

Active demand response or ADR, a particular form of demand side management, refers to all changes in electricity usage implemented directly by end-use consumers, thereby deviating from their normal consumption patterns, in response to certain signals, such as electricity prices. If these signals are timely and sufficiently strong, this could lead to, among other effects, a higher operational efficiency in production, transmission and distribution of electric power. Although there is a large potential for ADR identified in the literature, especially for ADR considering electric heating systems and thermal loads, there are still a number of obstacles to be overcome before a large scale roll-out of ADR technologies can take place. Not in the least, researchers are not able to accurately quantify the benefits of ADR and to fully describe the interactions between the supply and demand side of the electric power system under ADR.

In order to quantify the operational effects of introducing such programs, we developed an integrated modeling approach in this paper. This model allows to capture the full integrated effect of ADR on the supply and demand side, as well as to quantify the benefits for the system. However, this comes at a significant computational cost. In order to reduce the computational effort, several simplified approaches have been investigated, such as price-elasticity-based models, virtual generator models, price-profile models and merit order models. In particular, the difficulty of representing storage type customers' behavior by means of price elasticity based models was demonstrated, together with the complexity of a proper estimation of all terms contained in a virtual generator model. Furthermore, fixed electricity price profile demand side models, that neglect the interaction between supply side and demand side, can be misleading for the determination of the flexible demand behavior. Merit order models, instead, provide good results in terms of operational cost estimates, even if the supply side is represented in a simplified manner with respect to the integrated approach. Solving such a merit model takes about 30 seconds, compared to 30 minutes for the integrated model. A merit order model may thus be a good candidate for full year simulations.

The presented models may be used by other researchers who investigate the effect of ADR on the electric power system and the presented results may guide others in the development of their own models. Especially if one is interested in the effect of the market penetration of an ADR technology, the presented model could be useful. In addition, demand aggregators may use this work to develop operational models to schedule and optimize their use of thermostatically controlled loads in ADR programs.

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