Impacts of Strategic Behavior and Consumer Requirements on the Promise of Demand Response

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Abstract

Demand response (DR) is envisaged to be of significance for enhancing the flexibility of power systems. The distributed nature of demand-side resources necessitates the need of an aggregator to represent the flexible demand in the electricity market. This paper presents a bilevel optimization model considering the optimal operation of a strategic aggregator in a day-ahead electricity market. Additionally, consumers' requirements in terms of comfort satisfaction and cost reduction are considered by integrating detailed demand models and retail contract constraints. The results on the considered test system reveal that centralized optimization models would tend to over-estimate the capabilities of DR in an electricity market with strategic participants. Also, the flexibility value of DR for the power system and the profitability of the aggregator are significantly dependent on the retail contracts between the aggregator and the consumers, highlighting the need for careful contract design.

1. Nomenclature

Indices

j	Time index
k	Retail price discretization index
n	Archetype index
g	Conventional generator index

Constants:

$T_{n,r}^{min}, T_{n,r}^{max}$	Minimum and maximum indoor temp.
O_n^j	Occupancy profile
Δj	Time step
$\Delta\pi$	Retail price discretization step
η_n	Energy retention parameter of RTES
η_S	Charging efficiency of pumped storage
α_n	No. of buildings for each archetype
$\pi^{min}. \pi^{max}$	Minimum and maximum retail price
β	Consumer cost reduction parameter
ψ_D^j	Fixed demand bids
ψ_g^j	Conventional generation marginal cost
J	Optimization time horizon
G	Number of generating units
N	Number of building archetypes
K	Number of discretization steps

Variables:

P_{LA}^j	Total power consumption of load aggregator
π^j	Retail price
λ^j	Electricity SMP
$T_{n,r}^j$	Indoor room temperature
$Q_{n,heat}^j$	Total heat input to building
Q_n^j	Active heat output of RTES
$Q_{n,loss}^j$	RTES storage heat losses
P_n^j	Power consumption of RTES
E_n^j	Storage level of RTES
P_g^j	Output of conventional generators
$P_{S,d}^j$	Discharged power by pumped storage
$P_{S,c}^j$	Charging power of pumped storage
E_S^j	Storage level of pumped storage

2. Introduction

Effective Demand Response (DR) can yield several benefits including lower electricity generation costs, reduced investments in generation, transmission and distribution assets, and alleviation of the challenges attributed to large-scale grid integration of variable renewables [1].

A number of system-wide impact studies regarding demand flexibility have been reported in literature. For example, authors in [2], [3] show that temporal shifting of a price responsive load can potentially improve the economic operation of the power system. Recent studies have incorporated more detailed demand models in conventional centralized power system models (Unit Commitment/Economic Dispatch (UC/ED)) to assess the value of DR. The energy arbitrage potential of residential thermal loads has been evaluated in [4], [5], while flexibility of electric vehicles (EVs) has been discussed in [6], [7]. These integrated models highlight the importance of using detailed demand models in

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terms of capturing the impacts of load shifting on the consumers and also on the supply mix and electricity prices. However, these centralized models assume a perfectly competitive market and, thus, do not take into account the strategic behavior and objectives of the various market players.

The distributed nature of the large number of individual demand-side resources poses challenges for representing the flexibility and strategic objectives of these resource-owners (consumers) in the electricity market. Therefore, distributed demand-side resources are typically managed by load aggregators (LA), which act as intermediary agents between the consumers and the electric utility (e.g. the Transmission System Operator (TSO)). Although some demand-side resources (e.g. large industrial consumers) do not need LAs by virtue of the significant magnitude of their demand, however, here we focus on the general case of small-scale distributed demand-side resources which need to be coordinated for meaningful representation in the electricity market. The introduction of LAs, however, has given rise to several questions regarding the operation of LAs and their impacts on consumer welfare and system performance.

Several studies have presented models focusing on the optimal operation LAs, subject to constraints on the flexible demand. An end-to-end business model for a profit maximizing aggregator is presented in [8]. The aggregator manages its portfolio of the population of DR participants and variable wind generation resource, and determines bids to place in the day ahead wholesale market. An optimization model for simultaneous allocation of frequency services and energy arbitrage for a fleet of Thermostatically Controlled Loads (TCLs) managed by an aggregator is presented in [8]. Similarly, LA-focused models for optimal control of Plug-in Electric Vehicles are presented in [9], [10]. Recently, papers considering the game-theoretic (Stackelberg) interaction between LAs (leaders) and the consumers (followers) for domestic thermal loads and PEVs [11] - [13] have been reported in the literature. These papers represent the LA as a profit-maximizing entity, which determines optimal retail prices for consumers, while consumers aim to minimize their costs subject to those retail prices. Although the aforementioned studies provide valuable operating frameworks for LAs, they tend to isolate the impact of the aggregator's actions from the operation of the power system. This is because these studies consider electricity price as an exogenous parameter to the LA's optimization problem and therefore, cannot account for the feedback impact of the change in demand on electricity prices.

Papers considering strategic LA bidding in the electricity markets taking into consideration the impact of LA's actions on the power system are rare with the exception of [14], [15]. These papers present bilevel models for considering the operation of a strategic LA controlling a fleet of PEVs. In these models, the LA aims to minimize its costs in the upper level, while at the lower level, the total welfare of all market participants is maximized. The results presented in these papers highlight the importance of modelling the LA as a strategic market player and of considering the impact of LA's actions on the power system. However, as the objective of the LA in these models is to minimize its costs instead of maximizing profits, the proposed models do not capture the impacts of aggregator's actions and the retail contracts on the financial welfare of PEV owners.

This paper explores the impacts of considering the consumers' financial welfare in addition to their comfort constraints on the operation of a profit maximizing LA (also assumed to be the retailer for the consumers). The LA manages the space heating demand of consumers with residential thermal electric storage (RTES) devices. RTES devices contain a highly insulated solid thermal energy storage core which enables the conversion of electrical energy into thermal energy stored in an efficient manner for use at a later time [5]. When equipped with communications and control architecture, these devices can enhance power system flexibility by virtue of decoupling the scheduling of electric power demand from the time of thermal energy end-use. Such smart RTES technology is not only viable but also commercially available and deployed in several countries including Ireland, UK, France and the Nordic countries etc. [17].

Additionally, we demonstrate the drawbacks of using exogenous price based models in terms of isolating the impacts of the actions of the LA from system operation. In summary, this paper extends the state-of-the art through the following contributions:

1. A bilevel optimization model is implemented for optimal operation of a LA in an electricity market which is cleared based on social welfare maximization.
2. Detailed thermal demand state-space models are utilized to capture buildings' thermal dynamics and end-user comfort constraints associated to the RTES devices controlled by the LA.
3. Formulation of optimal retail prices by the LA subject to consumers' financial welfare constraints is integrated in the bilevel model to capture the impacts of various retail contracts on LA's profitability, consumer welfare and system performance.

The paper is structured as follows. Section 3 presents the mathematical formulation and linearization of the bilevel optimization problem. Section 4 discusses the results of an illustrative example and Section 5 concludes the paper.

3. Model formulation

In this section, we present the optimization model of a LA, which participates in the day-ahead electricity market (conducted by the system operator (SO)) on behalf of consumers with RTES space heating devices. In a competitive market, a strategic LA would aim to maximize its total welfare, which depends on the electricity System Marginal Price (SMP), accepted demand bids, the retail price set by the LA and the heating requirements of the consumers. However, the SMP is not only dependent on the actions of the LA, but also of the other participants in the market clearing process conducted by the SO. Therefore, the LA's optimization problem is constrained by the outcome of the market clearing process. This problem exhibits a bilevel structure, where the LA maximizes its welfare in the upper-level problem and the market clearing process is represented in the lower-level problem.

3.1. Consideration of consumers' welfare

As mentioned above, the LA manages the consumers' RTES space heating devices. It is assumed that the consumers have direct load control (DLC) contracts with the LA, which allow the LA to control the RTES devices of residential consumers. Such contracts exist for both residential and commercial customers in several European and North American countries [18] - [19]. It is also assumed that the total welfare of the consumers comprises of the satisfaction of their thermal comfort and the increase in their financial welfare (i.e. reduced heating costs).

Consumers' thermal comfort is dependent on the indoor temperatures, which must be within the comfort range specified by the consumers. Therefore, the thermal comfort constraints of the consumers are incorporated by modelling the evolution of indoor temperatures using detailed thermal dynamics models of a number of building archetypes. It is assumed that the aggregate thermal behavior of all the dwellings managed by the LA can be represented using a few building archetype models [20]. The building thermal dynamics are modelled using lumped parameter building models (RC thermal networks). Initially, the detailed building performance models for the considered archetypes are developed in the EnergyPlus simulation platform to generate the synthetic thermal dynamics data [20]. The synthetic data is then utilized to calibrate the lumped parameter models using the calibration methodology presented in [21]. After expanding the heat balance equations for all the nodes, re-ordering terms, and discretizing the resulting continuous-time model, the building energy model can be represented by the state-space equation [5]:

$$x_n^{j+1} = A_n x_n^j + B_{n,u} Q_{n,heat}^j + B_{n,d}\left[T_{amb}^j Solar_{West}^j Solar_{North}^j T_{hall}^j\right] \tag{1}$$

where, x_n^j is state vector representing the temperatures at different nodes of the archetype, and $A_n, B_{n,u}$ and $B_{n,d}$ are the state, input and disturbance matrices, respectively for archetype n at time interval j. The total heat provided by heating devices for the corresponding nodes of the archetype is incorporated in terms of $Q_{n,heat}^j$ which is defined as follows:

$$Q_{n,heat}^j = Q_n^j + Q_{n,loss}^j \tag{2}$$

where, Q_n^j is active heat power output and $Q_{n,loss}^j$ are the thermal storage losses of the RTES devices. Further details about the residential thermal modelling can be found in [5] and [21].

The nature of DLC contracts between the consumers and the LA entails that the consumers report their initial RTES charge levels and occupancy profiles to the LA at the start of the day. However, access to direct control of the devices and consumer information can result in the LA acting as an exploitative monopolistic retailer, resulting in loss of financial welfare (higher costs) for the consumers. Indeed, analysis of the Norwegian retail market has shown evidence of electricity retailers exhibiting monopolistic behavior by exploiting the passivity of some of their customers [22]. The consumers, on the other hand, would expect reduction in their costs as a compensation for giving up their privacy and control on the flexible RTES devices. Therefore, the retail contract design should take into consideration cost reduction for the consumers and prevent their exposure to exploitative retail prices by the LA. These consumer welfare related constraints are formulated and integrated in the LA's optimization model described in Section 3.2.

3.2. Load aggregator's problem

As discussed earlier, the LA is a strategic market participant, aiming to maximize its welfare. We assume that the LA maximizes its profits in order to achieve welfare maximization. The LA's optimization problem is formulated as follows:

$$\max \sum_{j=1}^{J} P_{LA}^j (\pi^j - \lambda^j) \tag{3}$$

$$\text{arg max}: P_{LA}^j, \pi^j, T_{n,r}^j, P_n^j, Q_n^j, Q_{n,loss}^j, E_n^j$$

subject to the following constraints:

$$T_{n,r}^{min}.O_n^j \le T_{n,r}^j.O_n^j \le T_{n,r}^{max}.O_n^j, \tag{4}$$

$$\forall j \in [1, J], \forall n \in [1, N]$$

$$E_n^{j+1} = E_n^j + P_n^j.\Delta j - Q_n^j - Q_{n,loss}^j, \quad \forall j \in [1, J], \forall n \in [1, N] \forall j, \forall n \tag{5}$$

$$Q_{n,loss}^j = (1 - \eta_n).E_n^j, \forall j \in [1, J], \forall n \in [1, N] \tag{6}$$

$$0 \le Q_n^j \le Q_n^{max}, \quad \forall j \in [1, J], \forall n \in [1, N] \tag{7}$$

$$0 \le P_n^j \le P_n^{max}, \quad \forall j \in [1, J], \forall n \in [1, N] \tag{8}$$

$$0 \le E_n^j \le E_n^{max}, \quad \forall j \in [1, J], \forall n \in [1, N] \tag{9}$$

$$P_{LA}^j = \sum_n \alpha_n.P_n^j, \quad \forall j \in [1, J], \forall n \in [1, N] \tag{10}$$

$$\pi^{min} \le \pi^j \le \pi^{max}, \qquad \forall j \in [1, J] \tag{11}$$

$$\frac{1}{J}\sum_{j=1}^{J} \pi^j \le \frac{1}{J}\sum_{j=1}^{J} \lambda^j \tag{12}$$

$$\sum_{j=1}^{J} P_{LA}^j.\pi^j \le \left(\frac{100-\beta}{100}\right)\sum_{j=1}^{J} P_{inflex}^j.\pi_{inflex}^j \tag{13}$$

The objective function (3) of the LA's optimization problem maximizes the day-ahead sum of its profits, which is defined as the difference between LA's revenue from selling energy to its consumers ($P_{LA}^j.\pi^j$) and its energy procurement costs from the day-ahead electricity market ($P_{LA}^j.\lambda^j$).

Consumers' thermal comfort and RTES technical constraints are modelled in Eqs. (4) – (9). Eq. (4) constrains the room temperature ($T_{n,r}^j$) to be within the thermal comfort limits during active occupancy periods. $T_{n,r}^j$ is determined using the state space model described in Section 3.1. Eq. (5) models the evolution of the storage level of the RTES devices, while storage losses of RTES are calculated using (6). Eqs. (7) - (9) constrain the active heat output, electric power input and storage level of the RTES devices to be within their respective rated values. Finally, the total electricity consumption of the LA (P_{LA}^j) is described in (10) as the scaled up summation of the electricity consumption by each archetype, where the scaling factor (α_n) is the total number of dwellings belonging to archetype *n*. Note that as mentioned above, the heating requirements determined by the representative archetype models are assumed to be representative of the total heating requirements of the LA-controlled dwellings.

Consumers' financial welfare constraints are incorporated by specification of the parameters of the retail contract between the consumers and the LA in (11) – (13). The constraints expressed in (11) restrict the retail prices (π^j) to be within an agreed range to prevent the consumers from being exposed to exploitative retail prices. Additionally, (12) ensures that the average retail price throughout the day should be less than the average SMP of electricity for that day. Finally, constraint (13) specifies that the total daily electricity cost incurred by the consumers ($\sum_j P_{LA}^j.\pi^j$) should be at least an agreed percentage (β) less than the costs the consumers paid when the RTES devices were operated as a fixed inflexible demand ($\sum_j P_{inflex}^j.\pi_{inflex}^j$), i.e. the consumer costs before the introduction of the LA. In order to determine the electricity consumption by the RTES devices before the introduction of the LA (P_{inflex}^j), it is assumed that the consumers previously operated their RTES devices as night-time storage loads. This assumption is justified by the fact that over the past few decades, residential thermal storage loads have conventionally been charged during the night-time in order to exploit the low off-peak tariffs [23]. Under this night-time charging scheme, all the RTES devices charge at their rated power (P_n^{max}) from 00:00 to 07:00 until they are fully charged or until the night period ends. The fixed night time tariff (π_{inflex}^j) is determined in this paper by averaging the annual electricity SMPs (corresponding to hours 00:00 to 07:00)) obtained using the market clearing model presented in Section 3.3., keeping $P_{LA}^j = P_{inflex}^j$.

3.3. Market clearing process

The market clearing process, conducted by the SO, is a social welfare maximization model. It is assumed that based on historical market participation data and forecasting techniques, the LA can estimate the bids of other market participants [15]-[16]. Additionally, the technical details of the generating units can be accessed based on the reports published by the system operators. The market clearing process is formulated as the following optimization problem, with the corresponding Lagrange multipliers mentioned next to each constraint:

$$\min \sum_{j=1}^{J}\left(-\psi_D^j.P_D^j + \sum_{g=1}^{G}\psi_g^j.P_g^j - \psi_{LA}^j.P_{LA}^j\right) \tag{14}$$

$$\text{arg min}: P_g^j, P_{LA}^j, P_{S,d}^j, P_{S,c}^j, E_S^j, \lambda^j$$

subject to:

$$\sum_{g=1}^{G} P_g^j + P_{S,d}^j = P_D^j + P_{LA}^j + P_{S,c}^j \;:\lambda^j, \quad \forall j \in [1, J] \tag{15}$$

$$0 \le P_g^j \le P_g^{max} \;:\mu_{min,g}^j, \mu_{max,g}^j, \tag{16}$$

$$\forall j \in [1,J], \forall g \in [1,G]$$

$$0 \leq P_{LA}^{j} \leq P_{LA}^{max} : \mu_{min,LA}^{j}, \mu_{max,LA}^{j}, \quad \forall j \in [1,J] \tag{17}$$

$$E_{S}^{j} = E_{S}^{j-1} + P_{S,c}^{j}.\eta_{S} - P_{S,d}^{j} \ : \mu_{S,E}^{j}, \quad \forall j \in [1,J] \tag{18}$$

$$0 \leq P_{S,c}^{j} \leq P_{S,c}^{max} : \mu_{min,S,c}^{j}, \mu_{max,S,c}^{j}, \quad \forall j \in [1,J] \tag{19}$$

$$0 \leq P_{S,d}^{j} \leq P_{S,d}^{max} : \mu_{min,S,d}^{j}, \mu_{max,S,d}^{j}, \quad \forall j \in [1,J] \tag{20}$$

$$0 \leq E_{S}^{j} \leq E_{S}^{max} : \mu_{min,E}^{j}, \mu_{max,E}^{j}, \quad \forall j \in [1,J] \tag{21}$$

The objective function (14) of the market clearing model maximizes the total welfare of the market participants based on their bids (ψ) and scheduled power consumption/generation. For the sake of simplicity, it is assumed that P_{D}^{j} represents the fixed inflexible electricity demand in the market. Eq. (15) models the power balance constraint, which ensures that the total generation by conventional generators (P_{g}^{j}) and the power discharged by the large-scale storage unit ($P_{S,d}^{j}$) should satisfy the sum of the inflexible load (P_{D}^{j}), the flexible load represented by the aggregator (P_{LA}^{j}) and the charging load of the storage unit ($P_{S,c}^{j}$). In this study, we have modeled a pumped hydro unit as the large-scale storage unit. It can be noted that the Lagrange multiplier of the power balance constraint represents the market clearing price of electricity. Eq. (16) limits the power generation of the conventional generators to be within their minimum and maximum values, respectively, while (17) restricts the LA's power consumption to be within the minimum and maximum limits. The maximum power consumption limit for the LA (P_{LA}^{max}) is defined as $\sum_{n} P_{n}^{max}$. The evolution of the storage level (E_{S}^{j}) in the pumped storage unit is modeled in (18), while technical constraints of this pumped storage unit are expressed in (19) – (21).

3.4. Formulation of the bilevel model

As discussed earlier, the optimal strategic operation of the LA can be formulated as a bilevel optimization model, with the upper level (UL) corresponding to the LA's optimization problem and the lower level (LL) corresponding to the market clearing process. This section describes the formulation of this bilevel problem into an equivalent single-level problem and subsequent linearization of this single-level problem.

As the LL problem is linear, it can be guaranteed that any solution which satisfies its Karush-Kuhn-Tucker (KKT) conditions would also be the optimal solution of the problem [24]. Therefore, we replace the LL market clearing process with its KKT stationarity and complementarity slackness conditions. However, the complementarity slackness conditions are nonlinear. These conditions are then linearized based on the Fortuny-Amat transformations [25], by introducing binary variables and large constants. The detailed mathematical formulation of the stationarity conditions and the linearization of the complementarity slackness conditions of the market clearing process using Fortuny-Amat transformations can be referred to in [15], which has a similar implementation.

The remaining non-linearities in the optimization problem are in the objective function (3) of the LA, which includes bilinear terms for LA's revenue ($P_{LA}^{j}.\pi^{j}$) and LA's costs ($P_{LA}^{j}.\lambda^{j}$). The revenue term can be linearized by implementing a discretized approximation of the retail price π^{j} as follows:

$$\pi^{j} = \pi^{min} + \Delta\pi.\sum_{k=1}^{K} \xi_{k}^{j} \tag{22}$$

$$\xi_{k}^{j} \leq \xi_{k-1}^{j} \ \forall k \in [2,J] \tag{23}$$

where, $\pi^{min}$is the minimum retail price, $\Delta\pi$ is the retail price step ($\frac{\pi^{max}-\pi^{min}}{K}$) and ξ_{k}^{j} are the binary variables for each discrete step, indexed by *k*. Using this discretization, the revenue term can be written as:

$$P_{LA}^{j}.\pi^{j} = P_{LA}^{j}.\pi^{min} + \Delta\pi.\sum_{k=1}^{K} P_{LA}^{j}.\xi_{k}^{j} \tag{24}$$

Next, we define a new variable $\omega_{k}^{j} = P_{LA}^{j}.\xi_{k}^{j}$, which leads to the equation:

$$P_{LA}^{j}.\pi^{j} = P_{LA}^{j}.\pi^{min} + \Delta\pi.\sum_{k=1}^{K} \omega_{k}^{j} \tag{25}$$

The term ω_{k}^{j} can be transformed into the following linear constraints using a large constant (M^{π}):

$$0 \leq \omega_{k}^{j} \leq \xi_{k}^{j}.M^{\pi}, \forall j \in [1,J], \forall k \in [1,K] \tag{26}$$

$$0 \leq P_{LA}^{j} - \omega_{k}^{j} \leq \left(1-\xi_{k}^{j}\right).M^{\pi}, \forall k \in [1,K] \tag{27}$$

The remaining bilinear cost term ($P_{LA}^{j}.\lambda^{j}$) can be linearized by using the strong duality theorem, according to which the primal and dual objectives are equal at optimality [26]. Therefore, the strong duality theorem allows exact linearization of the LA's cost term. Applying the strong duality theorem and using the stationarity and complementarity slackness conditions of the LL problem yields:

$$\lambda^j . P_{LA}^j = -\psi_D^j . P_D^j + \sum_g \psi_g^j . P_g^j + \lambda^j . P_D^j + \sum_g \mu_{max,g}^j . P_g^{max} - \mu_{S,E}^1 . E_S^0 + \mu_{max,S,c}^j . P_{S,c}^{max} + \mu_{max,S,d}^j . P_{S,d}^{max} + \mu_{max,E}^j . E_S^{max} \quad (28)$$

Using (25) and (28), the linearized reformulated single-level problem becomes:

$$\max \left(P_{LA}^j . \pi^{min} + \Delta\pi . \sum_k \omega_k^j\right) - \left(-\psi_D^j . P_D^j + \sum_g \psi_g^j . P_g^j + \lambda^j . P_D^j + \sum_g \mu_{max,g}^j . P_g^{max} - \mu_{S,E}^1 . E_S^0 + \mu_{max,S,c}^j . P_{S,c}^{max} + \mu_{max,S,d}^j . P_{S,d}^{max} + \mu_{max,E}^j . E_S^{max}\right) \quad (29)$$

subject to (4)-(13), (15)-(21), KKT stationarity conditions, Fortuny-Amat linearization of KKT complementarity conditions, and (22)-(27). The resulting single-level optimization problem lies in the category of Mixed Integer Linear Programming (MILP) which, although is non-convex because of the presence of binary variables, but, can be solved efficiently using commercial solvers.

4. Results and Discussion

This section discusses the preliminary results obtained using the proposed bilevel model on the impacts of strategic behavior and consumer constraints on the welfare of the various entities involved. Additionally, some insightful results highlighting the potential drawbacks of exogenous price based models as compared to integrated models are presented.

4.1. Test system

The developed bilevel model has been used to conduct an annual analysis of consumer welfare, LA's profitability, and system performance under various scenarios. The conventional generation portfolio of the test system including the number of units and marginal costs have been modelled according to [27]. The installed generation capacities have been adjusted according to the system peak load requirements. The bids of the generating units are assumed to be equal to their marginal costs. System inflexible demand profiles are obtained using normalized system demand profiles for the Irish power system for the year 2009 [28]. These normalized profiles are scaled up keeping 7.2 GW as the system peak load. The parameters of the two pumped hydro units are modelled according to [29]. To model the residential space heating demand, three Irish midflat archetypes based on different periods and materials of construction are considered. The total number of midflats considered is circa 70,000 [20] and the thermal modelling assumptions, and RTES technical characteristics are modelled as described in [5].

The following models are implemented to compare and understand the impacts of integrated and bilevel modelling on system performance and LA profitability.

1. *Centralized – Inflexible RTES demand (C-IFD):* The generation and RTES charging schedules are obtained using the centralized market clearing model (Section 3.3.), with integrated building models [5] but with RTES devices operating as night-time storage.
2. *Centralized – Flexible RTES demand (C-FD*): The generation and RTES charging schedules are obtained using the centralized market clearing model (Section 3.3.), with integrated building models and keeping RTES demand flexible. As this model study determines RTES charging schedules through non-strategic centralized dispatch, it represents the optimal usage of RTES flexibility from the system's perspective.
3. *Exogenous prices – Cost minimization (E-CM):* The LA takes exogenous electricity SMPs as input to its optimization model (Section 3.2.), which minimizes the LA's total cost.
4. *Bilevel – Cost minimization (B-CM):* The strategic market operation of the LA is considered using the bilevel model described in Section 3.4., keeping cost minimization as LA's objective.
5. *Bilevel – Profit Maximization (B-PM):* The strategic market operation of the LA is considered using the bilevel model described in Section 3.4., keeping profit maximization as LA's objective.

The contract parameters β, and the minimum and maximum retail price limits are taken as exogenous inputs in the model. For the base case in all the models, the values of β = 20% (i.e. 20% consumer cost reduction), π^{min}= 30€/MWh (lowest marginal cost of conventional generators), π^{max}= 93€/MWh (highest marginal cost of conventional generators). In order to understand how different values of these contract parameters could affect the different stakeholders, a sensitivity analysis for β and π^{max} has been presented in Section 4.2. Additionally, the retail price is equal to SMP for the C-FD, E-CM and B-CM models, while it is equal to the night time tariff for the C-IFD model.

The models are implemented in GAMS and are solved at hourly resolution with a look-ahead horizon of 24 hours assuming perfect forecast. It must be noted that the assumption of perfect forecast might not be realistic for modelling the market clearing problem, especially with large penetration of variable renewable resources. However, this assumption has been made to ensure computational tractability of the bilevel model given the requirement of path dependent optimization for management of storage devices. Also, in the case study that follows, variable renewable resources are not included.

4.2. Importance of integrated modelling

Figure 1 shows the total power consumption of the LA and SMP for the E-CM and C-FD models in order to highlight the importance of using integrated models as compared to exogenous price-based models. The SMP profile from C-FD is used as input for the E-CM model and the resulting LA power consumption is fed back to the C-FD model to determine the impacts on SMP.

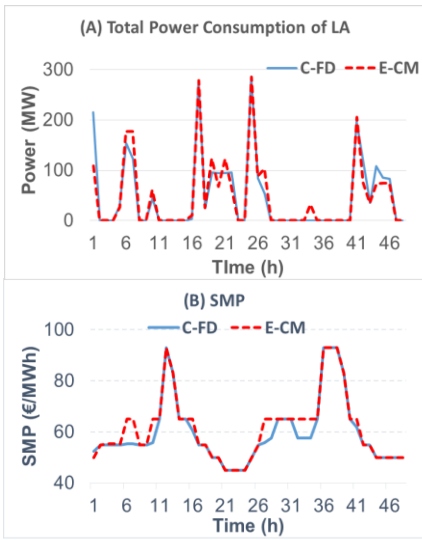

Figure 1. Importance of integrated modelling

It can be observed from panel (A) in Figure 1 that even though the objective of E-CM is to reduce LA costs, the resulting power consumption profile is different from C-FD. This is because the minimum cost solution for E-CM is not unique, therefore, several power consumption profiles can have the same cost for the LA while meeting the heating requirement (e.g. when input SMP is the same for several hours of the day). These differences in power consumption would be expected to be further increased when the LA would aim to maximize profits. The resulting impact on SMP is shown in panel (B) of Figure 1. It can be seen e.g. for hours 6 and 7 that the increased concentration of power consumption for the E-CM model would have a feedback impact on SMP resulting in higher prices as compared to those initially determined using C-FD. Changes in SMP also imply that exogenous price based models can also lead to additional start-ups and shut-downs of generation units, making the system operation less economical. Therefore, these results highlight the merits of using integrated models for analysis of flexible demand instead of exogenous price based models.

4.3. Impacts of strategic behavior

The impacts of the LA's strategic behavior on the consumers' welfare and the power system operation are depicted in Figure 2. It can be observed in panel (A) that in the inflexible night time storage model (C-IFD), the heating energy consumption for each house is very high compared to C-FD (approximately 64% of the energy consumption in C-IFD). This is because under night time operation, the RTES devices are fully charged every day irrespective of the daily heating requirement, making their operation very inefficient in terms of energy consumption. When aiming to minimize its costs (B-CM), the LA reduces the power it purchases and thus the results are almost identical to the centrally optimal values determined in C-FD. However, when maximizing profits (B-PM), the LA purchases much more energy from the electricity market in order to achieve the maximum possible revenue from selling the energy to the consumers. Therefore, it can be concluded that the profit maximization behavior of a LA with DLC would not be energy efficient. However, the energy consumption is still circa 2% lower than the inflexible C-IFD case as the LA is bound to reduce consumer costs due to constraint (13).

These differences in heating energy consumption profiles translate into differences in consumer costs as shown in panel (B). The results show that the consumers would have to pay only 39% of the costs they paid in the C-IFD case if the LA aims to minimize its costs (B-CM) and pass on all the cost reductions to the consumers. The profit maximization behavior (B-PM) expectedly results

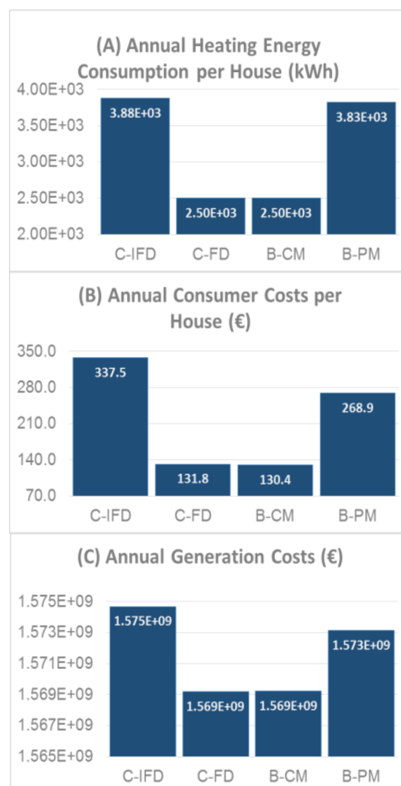

Figure 2. Impacts of LA's strategic behavior on consumer and svstem

in higher costs for consumers as the LA tries to maximize its revenues. However, the consumers still are better off when being controlled by a profit maximizing LA as compared to the inflexible night storage operation due to the cost reduction constraint (13). Indeed, the consumer costs are reduced by circa 20% as specified by the retail contract parameter β.

Finally, the impacts of strategic LA behavior on annual system generation costs are presented in panel (C). The performance of B-CM is again almost identical to the centralized C-FD as in order to minimize costs, the LA not only reduces the energy consumption but also purchases energy during low SMP periods, thereby aligning its performance with centrally optimized results. However, LA's profit maximization increases the system costs as compared to C-FD primarily because of the increase in energy consumption. However, B-PM can still achieve significant reduction in generation costs as compared to C-IFD. This is because in C-IFD, the RTES devices consume fixed amounts of energy irrespective of the system conditions while in B-PM, the LA purchases energy during periods of low SMP to increase its profit margin. These results highlight that the behavior and objectives of the LA can not only have significant implications for the consumers, but also on the power system operation. It must also be noted that the model presented in the paper assumes that the LA can manage the operation of all the RTES devices owned by the consumers who have chosen to enter the DLC contract. If some of the consumers choose to opt out from the DLC contract, the LA would have a reduced magnitude of controllable demand, which could translate into reduced profitability of the LA and increased system generation costs.

It can be concluded from the results presented above that centrally optimized results would not be valid in the presence of a strategic LA as they would tend to overestimate the system value of flexible load. Nevertheless, the presence of a profit maximizing LA is still beneficial for the system as compared to the loads being inflexible.

4.4. Impacts of retail contract design

As mentioned in Section 3, the LA has a direct load control (DLC) contract with the consumers subject to retail contract constraints (11) – (13). In this section, we explore the impacts of varying the retail contract parameters β (consumer cost reduction percentage) and π^{max}(maximum retail price) in the LA's profit maximization (B-PM) model.

It can be seen in panel (A) of Figure 3 that as the agreed consumer cost reduction increases (i.e. β increases), there is a significant reduction in heating energy consumption because the LA is bound to reduce the consumer costs. Additionally, as the maximum retail price (π^{max}) increases, there are some additional reductions in energy consumption. This is because increase in π^{max} allows the LA to purchase lesser energy without impacting the profitability (i.e. by charging higher prices to consumers for smaller volumes of energy). Therefore, restricting the LA's profitability by increasing β improves energy efficiency, while restricting the LA's profitability by reducing π^{max} would reduce the energy efficiency.

The impacts of the retail contracts on consumer costs are shown in panel (B). As expected, higher values of β, result in lower consumer costs as compared to the C-IFD model. It can also be observed that for a given value of β, the maximum retail price (π^{max}) does not have any noticeable impacts on consumer costs. This is because the LA only needs to reduce consumer costs by β%, so for smaller values of π^{max}, the LA purchases more energy in order to offset the impact of reduced π^{max}.

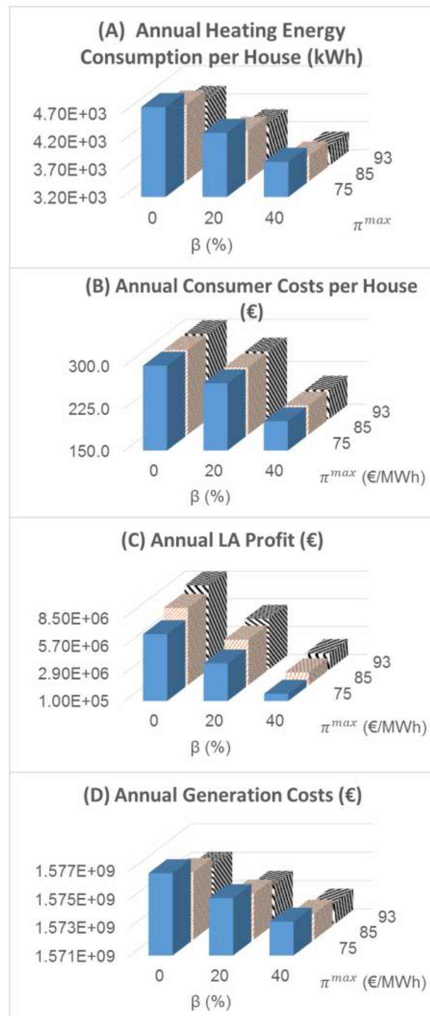

Figure 3. Importance of the specification of retail contract parameters

Panel (C) presents the impacts of the retail contracts on LA's profitability. It can be noticed that β has a very significant impact on LA's profits as an increase in β from 0% to 40% reduces the LA's profits by circa 80%. This can be explained by the fact that reduction in β reduces the LA's revenue, while the LA's cost reduction by reducing energy consumption is bounded by consumer's thermal comfort requirements, thereby resulting in much lower profits. For a given value of β, increase in π^{max} allows the LA to achieve increase in profits as the LA can purchase energy only during periods of low SMP and charge higher retail prices to the consumers.

Finally, the impacts on system generation costs are shown in panel (D). The generation costs profile mirrors the heating energy consumption profile shown in Panel (A). As discussed earlier, increasing β and increasing π^{max} force the LA to be energy efficient and to purchase energy during periods of low SMP, respectively, thereby reducing the system generation costs, and thus driving the results towards centrally optimal values.

The analysis presented above leads to the conclusion that for contracts involving direct load control (DLC), β has a much greater impact on consumers', LA's and system's welfare as compared to π^{max}. Additionally, contrary to intuition, allowing the LA to charge higher retail prices would be socially beneficial under DLC contracts. This is due to the fact that increasing π^{max} for a given value of β doesn't impact the consumers' welfare, but results in higher profits for the LA and lower system generation costs, thereby improving the net social welfare.

5. Conclusion

This paper presented a novel bilevel formulation for understanding the impacts of the strategic behavior of a profit maximizing load aggregator (LA) in the electricity market while being constrained by consumers' welfare based on retail contract specifications. The results of the bilevel model were compared with other models including centralized and exogenous price based models. The results depicted the drawbacks of exogenous price based models in terms of not being able to capture the feedback impact of change in demand on electricity price. Additionally, based on the preliminary results for the considered test system presented in this paper, it was observed that the strategic profit maximizing behavior of the LA results in deviation of system performance from centrally optimized results, thereby indicating that centralized models would tend to overestimate the system value of demand response. Finally, the need for carefully designing the retail contract parameters was highlighted, as they not only affect the welfare of the consumers and the LA but also the operation of the power system.

Future work would present more detailed results using the proposed model and present some additional sensitivities of other important parameters. Additionally, the market clearing problem presented in this paper doesn't incorporate variable renewable resources. The inclusion of these resources would require consideration of the uncertainty associated to the prediction of these resources. Moreover, consumer opt-out contingency could also be formulated as a stochastic event with a certain probability distribution. Therefore, the framework presented in this paper could be extended by formulating it as a stochastic optimization problem and considering the impacts of uncertainty on the value of aggregator-controlled flexible demand. Additionally, it would also be interesting to explore the operation of the LA when it simultaneously participates in provision of ancillary services in addition to energy arbitrage.

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