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# Bonus-Based Demand Response Using Stackelberg Game Approach for Residential End-Users Equipped with HVAC System

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***Abstract*—This paper proposes a novel Stackelberg game approach for activating demand response (DR) program in a residential area aiming at addressing the mismatch between the demand and renewable energy generation. In this study, two major players, namely the aggregator as a leader and the consumers as followers, are considered. The aggregator, which owns a wind farm and also receives power from the independent system operator (ISO), strives to obtain the maximum matching between the consumers' demand and forecasted wind power by incentivizing consumers to adjust their load through offering a bonus to them. On the other hand, consumers change their load profiles for obtaining the highest amount of bonuses. Each consumer has two kinds of loads including critical loads, which must be maintained under any circumstances, and the flexible loads, e.g., heating, ventilation, and air conditioning (HVAC) system, which can be regulated for DR purposes. In order to consider the uncertainty associated with the wind generation and the demands, a scenario-based stochastic programming model has been adopted in this work. Results show the effectiveness of the Stackelberg game model used for interaction between the aggregator and consumers, and the best response that can be served to both of them.**

***Index Terms*—Bilevel programming, demand response, HVAC systems, Stackelberg game, strong duality theorem.**

## NOMENCLATURE

### *A. Indexes and Sets*

| | |
|---|---|
| $t$ | Time period index |
| $n$ | House index |
| $y^+$ | Slope index for linearization of $(\Delta P_{n,t}^{hvac+})^2$ |
| $y^-$ | Slope index for linearization of $(\Delta P_{n,t}^{hvac-})^2$ |
| $T$ | Index set of the time period |
| $N$ | Index set of houses |
| $Y^+$ | Index set of the piecewise linearization for $\left\|\Delta P_{n,t}^{hvac}\right\|$ |
| $Y^-$ | Index set of the piecewise linearization for $\left\|\Delta P_{n,t}^{hvac}\right\|$ |

### *B. Parameters*

| | |
|---|---|
| $P_{0,n,t}^{hvac}$ | HVAC power for the case without demand response. |
| $P^w$ | Active power generated by wind turbine $(W)$ |
| $P_r$ | Rated power of wind turbine $(W)$ |
| $w_w$ | Wind speed $(m/s)$ |
| $w_r$ | Wind speed at rated power $(m/s)$ |
| $w_c$ | Cut-in wind speed $(m/s)$ |
| $a$ | Slope of the wind power curve |
| $K$ | constant |
| $P_{n,t}^{cr}$ | Hourly expected non-HVAC load of house n $(W)$ |
| $P_t^w$ | Hourly expected wind power $(W)$ |
| $H_y$ | Thermal conductance allowing the $C_m$ to be connected in the mass node point $(W/°C)$ |
| $H_x$ | thermal conductance of ventilation air heat $(W/°C)$ |
| $H_g$ | thermal conductance between $T^g$ node point and $T^a$ $(W/°C)$ |
| $H_e$ | Virtual thermal conductance between $T^a$ and $T^e$ node points $(W/°C)$ |
| $H_m$ | Thermal conductance allowing the $C_m$ to be connected in the mass node point $(W/°C)$ |
| $T_{n,t}^{set}$ | Set point temperature for house $n$ at time $t$ $(°C)$ |
| $T_t^e$ | Outside ambient temperature at time $t$ $(°C)$ |
| $T_t^g$ | Ground temperature at time $t$ $(°C)$ |
| $T^x$ | Ventilation supply air temperature $(°C)$ |
| $\theta/2$ | Maximum value of upper and lower deviation from the set point temperature $(C^o)$ |
| $C_n^a$ | Heat capacity of the indoor air $(MJ/°C)$ |
| $C_n^m$ | Heat capacity of the building fabric $(MJ/°C)$ |
| $\Delta t$ | Duration of time slot (hours) |
| $P_n^{hvac\_ma}$ | Power rating of HVAC for house $n$ $(W/h)$ |
| $Q_n^{hvac\_mc}$ | Rated thermal power of HVAC for house $n$ $(W/h)$ |
| $SoC_n^{max}$ | Maximum amount of state of charge for thermal storage for house $n$ (%) |
| $SoC_n^{min}$ | Minimum amount of state of charge for thermal storage for house $n$ (%) |
| $\eta^c$ | Storage loss coefficient while charging |
| $\eta^d$ | Storage loss coefficient while discharging |
| $\pi_{sc}$ | Probability of each scenario for non-HVAC load |
| $\pi_{sw}$ | Probability of each scenario for wind generation |

### *C. Variables*

| | |
|---|---|
| $T_{n,t}^a$ | Indoor temperature for house $n$ at time $t$ (°C) |
| $T_{n,t}^m$ | Fabric temperature for house $n$ at time $t$ (°C) |
| $Bonus_{n,t}$ | Bonus amount given to house $n$ during time $t$ (€) |
| $P_{n,t}^{hvac}$ | HVAC Electrical power for house $n$ at time $t$ $(W)$ |
| $\Delta P_{n,t}^{hvac}$ | power change of HVAC for house $n$ at time $t$ $(W)$ |
| $Q_{n,t}^{hvac}$ | HVAC thermal power for house $n$ at time $t$ $(W)$ |
| $SoC_{n,t}^{hvac}$ | State of charge of thermal storage for house $n$ at time $t$ |
| $\xi_{n,t}$ | Storage thermal losses for house $n$ at time $t$ $(W)$ |
| $\Delta P_{n,t}^{hvac+}$ | Auxiliary variable for linearization of $\left\|\Delta P_{n,t}^{hvac}\right\|$ |
| $\Delta P_{n,t}^{hvac-}$ | Auxiliary variable for linearization of $\left\|\Delta P_{n,t}^{hvac}\right\|$ |
| $f_t$ | variable for linearization of absolute value |
| $b$ | Coefficient for bonus (€/Watt^2)( $10^{-6}$) |

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| | |
|---|---|
| $w$ | Uniting factor (€/Watt) |
| $\delta P_{y^{+}n,t}^{hvac+}$ | Maximum value in each slop for changing $\Delta P_{n,t}^{hvac+}$ |
| $\delta P_{y^{-}n,t}^{hvac-}$ | Maximum value in each slop for changing $\Delta P_{n,t}^{hvac-}$ |
| $m_{y^{+}n,t}^{+}$ | Slopes of the $y_{th}^{+}$ block of the HVAC power variation for house $n$ at time $t$ |
| $m_{y^{-}n,t}^{-}$ | Slopes of the $y_{th}^{-}$ block of the HVAC power variation for house $n$ at time $t$ |
| $w_{y^{+}y^{-}n,t}$ | Auxiliary variable for McCormick linearization for house $n$ at time $t$ |

*D. Dual variables*

$\lambda_{n,t}$, $\varphi_{n,t}$, $\beta_{n,t}^{up}$, $\beta_{n,t}^{lo}$, $\alpha_{n,t}$, $\mu_{n,t}^{up}$, $\mu_{n,t}^{lo}$, $\sigma_{n,t}$, $\iota_{n,t}^{up}$, $\iota_{n,t}^{lo}$, $\nu_{n,t}^{up}$, $\nu_{n,t}^{lo}$, $\rho_{n,t}$, $\varepsilon_{n,t}$, $\delta_{n,t}^{up}$, $\delta_{n,t}^{lo}$, $\upsilon_{t}^{up}$, $\upsilon_{t}^{lo}$

## I. Introduction

Developing advanced technologies for renewable energy sources (RESs) has recently resulted in high penetration of these resources into the power grid. The unpredictability of RESs, besides their fluctuating nature, may impose harmful effects on the existing power grid that has not been built to withstand such unstable conditions. Wind power generation is one of the RESs that has developed rapidly and will comprise a significant share of the power generation in the near future. The accessibility of wind power is very high almost everywhere, especially near the offshore locations that not only saves the land but also reduces the capital cost for establishing a wind power plant. However, the generated power by wind fluctuates substantially, and it needs to be taken into account properly [1]. On the other hand, the ever-increasing electricity power demand and its volatile nature create other challenges on the power grid that negatively affect its efficiency. To address this issue and to enhance the power grid efficiency, smart grid infrastructure and its applications play a key role [2].

In order to cope with the aforementioned issues, demand response (DR) programs are one of the most studied approaches that work by activating the participation of end-user consumers for matching the power generation and consumption as much as possible. Generally, DR can be categorized into two different types, including direct load control (DLC) and indirect load control. In the direct load control, which is an incentive-based approach and not a price-based one, an aggregator or distributed system operator (DSO) adjusts the consumers' power demand directly. This effective scheme has been widely used in frequency regulation [3] and peak load shaving [4], but it noticeably sacrifices the privacy of consumers and decreases their satisfaction level. On the other hand, the indirect load control is based on incentivizing consumers to contribute to the DR program in exchange for a reward or decreasing their electricity bill. This approach needs less infrastructure for monitoring and communication compared to the direct load control policy. Above that, by utilizing this plan, the comfort level of consumers is well maintained. In [5], a hierarchical market model has been presented to decrease the operational cost of the grid by giving incentives to the aggregator and providing compensation for the consumers. In that paper, the consumers were responsible for compromising between their receiving bonuses and comfort level. In [6], a smart pricing mechanism was proposed to activate the DR management program where an energy consumption controller for each consumer was introduced at the presence of a communication infrastructure for a two-way connection between the utility and the consumers. In [7], a price-based DR program was investigated by adopting scenario-based stochastic optimization and robust optimization approaches via a mixed-integer linear programming problem. In [8], a two-stage robust programming method was presented to handle the coordination between price-based DR and multiple distributed generation (DG) units in the presence of uncertainty related to renewable DG and load consumption.

According to [9], the power consumption by residential consumers has increased, hitting nearly 55% of the total electricity usage in Europe in 2012. However, the DR programs have been mostly applied to the industrial and commercial sectors [10], due to the large demand requested by them and the fact that their load profile is highly predictable. Nowadays, thanks to the existing proper communication infrastructure, besides the extensive use of smart metering systems, there is a great interest in adopting DR programs at the residential level. In [11], a reward-based approach with the aim of peak shaving was suggested for residential end-users. It was supposed that the consumption details of consumers were recorded by questionnaires to provide necessary information for DR purposes, but it might be tedious and imprecise.

On the other hand, among various assortments of residential appliances, thermostatically controlled loads (TCLs) account as great potential for DR purposes, not only because of their fast response but also due to the thermal inertia which maintains their comfort level in an acceptable range while operating in interruptible mode (the period when the appliances curtail their power) [12]. In [13], the physical and operational features of various loads were analyzed for building the TCL model at the residential level. Amongst the diverse TCL loads available in regular households, heating, ventilation, and air conditioning (HVAC) systems have the most significant impact on the system stress due to the higher power consumption that contributes to the peak demand. Therefore, HVAC is the most effective and interesting option for implementing a DR program in a residential area. In [14], aiming at using the HVAC systems in the DR program, the aggregated characteristic of a group of HVAC units was investigated by studying their dynamic features. In [15], a new centralized controller with modern design and specifications was proposed for controlling TCL loads while a system including a thousand HVAC units was modeled for examining the effects of various parameters on the operation. In [16], a distributed DR approach and an extended Lyapunov optimization were proposed for residential houses to evaluate the capacity of their HVAC systems for alleviating the fluctuation of RES. In almost all of the aforementioned papers, only one entity such as aggregator, electricity market, or DSO wer the only decision-makers while neglecting the capability of consumers in making any decision. It means that they are mostly sacrificing the comfort level of consumers to reach their goal in the DR program via peak shaving or matching the consumers' load with their expected power generation.

In order to have a win-win condition for both the utility and the consumer sides, a proper interaction between them should be established. To this end and for the sake of practicality in activating the DR program, the interaction should follow the game theory concept. One of the most practical techniques is the Stackelberg game theory, which is a suitable option for handling hierarchical management problems in a smart grid to study the interaction between two players [17]. In [18], a two-stage Stackelberg game approach was adopted between a grid operator on a local scale and several load aggregators. A novel locational marginal price was used to activate the DR program by providing enough incentives for the loads aiming at following the fluctuant renewable energy generation. In [19], a game theory model was proposed to find the optimal time-of-use electricity pricing and the consumers' response as well. Nevertheless, it uses a backward induction method to find the solution, which suffers some drawbacks. Firstly, it does not reflect how players are actually playing. Secondly, as the players may not have a comprehension of what is happening, it may lead to a game of incomplete information, which is not solvable by backward induction. In [20], a game between utility service and consumers in a retail market scale was proposed to support the utility in finding the optimal solution and then incentivizing the consumers to adapt their electricity consumption. However, the DLC was used in that work, which sacrifices the privacy of consumers and prevents making a practical game in which both sides participate actively. A DR-based Stackelberg game between the electricity providers and the consumers was proposed in [21] where the electricity providers aimed at maximizing their benefits while the consumers were trying to minimize their electricity bills. Although this approach aids to have a more reliable power supply, the main downside would be a noticeable communication between consumers and utility companies which makes the smart grid more vulnerable to privacy issues. Instead, we considered the same concept of reformulation via the strong duality theory presented in [23]. In this method, it takes care of the privacy issues to some extent, although the privacy still remains questionable.

To cope with the aforementioned restrictions, this work proposes a bonus-based DR program via the Stackelberg game theory. It is supposed that there is one electricity provider as an aggregator and several houses as consumers. The aggregator who possesses a wind power plant tries to maximize the utilization of wind power by giving a bonus to the consumers. In contrast, the consumers seek to maximize the bonus received from the aggregator. Each house has a critical load which is not curtailable or shiftable to other time. In addition, the houses are equipped with HVAC systems that provide the possibility for contribution in the DR program by adjusting their load. For this reason, a two-capacity model of the HVAC system, which is highly accurate and efficient for DR application, is used [22]. Furthermore, a stochastic optimization problem with different scenarios has been considered for addressing the uncertainty associated with wind and demand. The key contributions of this paper are as follows.

1) The proposed approach maintains the comfort level of consumers to a great extent because each consumer is freely capable of changing their indoor temperature and also determining the maximum contribution in each hour.
2) An indirect load control scheme (bonus-based) is used for DR purposes where the participants will receive bonuses proportional to their contribution.
3) A Stackelberg game approach with *N* consumers, acting as followers, and one aggregator, as the leader, is expressed for considering the interaction between these players. The proposed game ends up in a bilevel programming model that allows both sides to actively participate in the game.
4) Finally, the strong duality theorem is adopted in this paper to deal with the bilevel problem. The original bilevel model is recast into an equivalent single-level problem by eradicating the iterative process in finding the optimal solution.

The rest of this paper is organized as follows. Section II introduces the Stackelberg game approach, including the leader and followers models. Problem formulation is provided in Section III. The simulation results are discussed in Section IV. Section V provides concluding remarks.

## II. Stackelberg Game Model

In this paper, the Stackelberg game theory is adopted with one leader (the aggregator) and *N* followers (the consumers) for activating the DR program in a residential area. In order to ease perception through this paper, the terms of "aggregator" and "leader", as well as "consumer", "house" and "follower" are interchangeably used. First, the interaction signals between the players, i.e., their strategy set or actions, are defined. The aggregator strategy set includes a bonus that should be allocated to the consumers, and the consumers' strategy is to change their electricity demand pattern according to the bonus. With these assumptions, the game will be started and proceeded in the following order. First, the aggregator announces the bonus to the consumers, and then the consumers choose an action, which is supposed to be the best response regarding the aggregator's strategy. At the following stage, each consumer submits its own actions to the aggregator and waits for a response from the aggregator, i.e., the aggregator will update its actions and send it back to the consumers. This interaction continues until the desired equilibrium is revealed. In the following, the aggregator and consumers models are explained in detail.

### A. Leader Model

In this paper, it is assumed that the aggregator works to minimize the mismatch between wind power generation and consumers' demand. In addition, it is supposed that the aggregator owns a wind power plant and tries to maximize the amount of energy, which it is capable of selling to the consumers in each hour. In the simulated case studies, the day 6th of January is considered for this purpose, and the wind speed data and non-HVAC load are predicted for the 24 hours ahead by the ARIMA model based on historical data of three months. Then, the scenario reduction technique has been used to constitute an appropriate trade-off between the modeling accuracy and computational tractability. The scenarios for the non-HVAC load and wind power, are considered to be equiprobable. Having wind speed data, and using a simple method for modeling the wind turbine, the generated power is estimated as in [23].

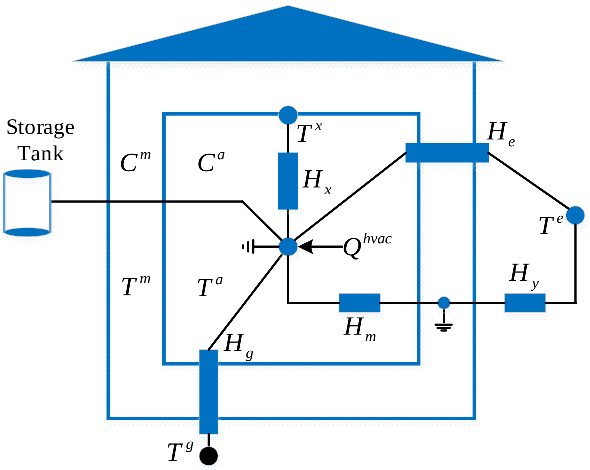


Fig. 1. The tandem of heat and storage model of the house

TABLE I.
THERMAL PARAMETERS RELATED TO HOUSES AND HVAC SYSTEMS

| Parameter | Value |
|---|---|
| $H_y, H_x, H_g, H_e, H_m$ | 0.33, 0.48, 0.05, 0.29, 5.16 (W/°C-m2) |
| $C_a, C_m$ | 13.02, 112.13, (kJ/C°-m$^2$) |
| $T^x$ | 18 C$^0$ |
| $P^{hvac,min}, P^{hvac,max}$ | 0, 7.5 kWh |
| $Q^{hvac,min}, Q^{hvac,max}$ | 0, 7.5 kWh |
| $\eta^c, \eta^d$ | 0.95 |
| $SoE_{min}, SoE_{max}$ | 30-3750 (Wh) |

Because the aggregator has no control over the wind speed and thereby the wind power generation, it would be beneficial for the aggregator to provide some bonus for consumers to incentivize them for changing their load profile in a way that increases the utilization of the wind power. In return, consumers receive a monetary reward according to their contribution level. Therefore, the objective function on the aggregator side is the sum of bonuses giving to the consumers. These two terms, as can be seen in (4), are different in nature and come with Watt and € units, respectively. For this reason, we allocated the uniting factor w (€/W) to uniform the units of these two terms. The objective function will be defined to minimize the power

$$P^w = \begin{cases} a.w_w + K, & w_c < w_w \quad and \quad w_r > w_w \\ P_r & w_w > w_r \end{cases} \tag{1}$$

$$a = P_r \big/ w_r - w_c \tag{2}$$

$$K = -a.w_c \tag{3}$$

mismatch between wind generation and consumers' load demand as (4).

$$\min(w\sum_{t=1}^{T}\left|\sum_{n=1}^{N}P_{n,t}^{cr}+P_{0_{n,t}}^{hvac}+\Delta P_{n,t}^{hvac}-P_t^w\right|+\sum_{t=1}^{T}\sum_{n=1}^{N}\left|\Delta P_{n,t}^{hvac}\right|bonus_{n,t}) \tag{4}$$

The first term in (4) shows the difference between the generated wind power and consumers' demand including the non-HVAC and HVAC loads. The second term stands for the multiplication of change in the HVAC power and the amount of bonus for that time. The aggregator strives to keep both these terms as minimum as possible.

### B. Follower Model

For the follower model, a residential area is considered in which the houses are equipped with a home energy management system (HEMS) for receiving the bonus information from the aggregator side. Furthermore, every house is supposed to have two different types of load, containing critical and flexible. The critical loads stand for those demands that should be satisfied under any circumstances, while the flexible loads are those adjustable demands that effectively contribute to the DR program. In this work, the HVAC system is considered as a manageable load, due to its high electricity demand and its adjustability. The consumers, after receiving the actions from the aggregator, react and select their best strategy. Suppose $\Delta P = \Delta P_{sc,sw,n,t}^{hvac}\ \forall n \in N, \forall t \in T$ in (4) and $bonus_{sc,sw,n,t} = b\left|\Delta P_{sc,sw,n,t}^{hvac}\right| : \forall n \in N, \forall t \in T$ in (5) are the strategy of consumers and aggregator, respectively, where $\Delta P_{sc,sw,n,t}^{hvac}$ indicates the power change of the HVAC system for every scenario, every house and every hour, and $bonus_{sc,sw,n,t}$ shows the amount of bonus paid by the aggregator to each consumer in each hour for every scenario. The bonus is a function of $\Delta P_{sc,sw,n,t}$, which means consumers will get a larger profit by contributing more to the DR program. Hence, the objective function for the consumers' side should be maximizing the total amount of bonus for all consumers, which is equal to the multiplication of the bonus for each hour by the demand change of the HVAC in that hour, as (5).

$$\max \sum_{sc=1}^{SC}\sum_{sw=1}^{SW}\sum_{n=1}^{N}\sum_{t=1}^{T}\pi_{sc}\pi_{sw}\left|\Delta P_{sc,sw,n,t}^{hvac}\right|bonus_{sc,sw,n,t} \tag{5}$$

$$T_{sc,sw,n,t}^{a}=\frac{T_{sc,sw,n,t-1}^{a}+[H_n^m T_{sc,sw,n,t-1}^m+H_n^e T_t^e+H_n^g T_t^g+H_n^x T^x+Q_{sc,sw,n,t}^{hvac}]\big/ c_n^a}{1+\Delta t(H_n^m+H_n^e+H_n^g+H_n^x)\big/ c_n^a}$$
$$:(\lambda_{sc,sw,n,t});,\forall sc\in SC,\forall sw\in SW,\forall t\in T,\forall n\in N \tag{6}$$

$$T_{sc,sw,n,t}^{m}=\frac{T_{sc,sw,n,t-1}^{m}+\Delta t[H_n^m T_{sc,sw,n,t-1}^a+H_n^y T_t^e]\big/ c_n^m}{1+\Delta t(H_n^m+H_n^y)\big/ c_n^m}$$
$$:(\varphi_{sc,sw,n,t});\forall sc\in SC,\forall sw\in SW,\forall t\in T,\forall n\in N \tag{7}$$

$$T_{n,t}^{set}-\frac{\theta}{2}\le T_{sc,sw,n,t}^{a}\le T_{n,t}^{set}+\frac{\theta}{2}:(\beta_{sc,sw,n,t}^{lo},\beta_{sc,sw,n,t}^{up});\forall sc\in SC,\forall sw\in SW,\forall n\in N,\forall t\in T \tag{8}$$

$$SoC_{sc,sw,n,t}=SoC_{sc,sw,n,t-1}+\left(\eta^c(P_{0_{n,t}}^{hvac}+\Delta P_{sc,sw,n,t}^{hvac})-Q_{sc,sw,n,t}^{hvac}\big/\eta^d\right)$$
$$-\xi_{sc,sw,n,t-1}:(\alpha_{sc,sw,n,t});\forall sc\in SC,\forall sw\in SW,\forall t\in T,\forall n\in N \tag{9}$$

$$SoC_{n,t}^{\min}\le SoC_{sc,sw,n,t}\le SoC_{n,t}^{\max}:(\mu_{sc,sw,n,t}^{lo},\mu_{sc,sw,n,t}^{up});$$
$$\forall sc\in SC,\forall sw\in SW,\forall t\in T,\forall n\in N \tag{10}$$

$$\xi_{sc,sw,n,t}=\eta_n.SoC_{sc,sw,n,t}:(\sigma_{sc,sw,n,t});\forall sc\in SC,\forall sw\in SW,\forall n\in N,\forall t\in T \tag{11}$$

$$\Delta P_n^{hvac-\min}\le\Delta P_{sc,sw,n,t}^{hvac}\le\Delta P_n^{hvac-max}:(\iota_{sc,sw,n,t}^{lo},\iota_{sc,sw,n,t}^{up});$$
$$\forall sc\in SC,\forall sw\in SW,\forall n\in N,\forall t\in T \tag{12}$$

$$0\le\Delta P_{sc,sw,n,t}^{hvac}\le P_n^{hvac\_max}-P_{0_{n,t}}^{hvac}:(\nu_{sc,sw,n,t}^{lo},\nu_{sc,sw,n,t}^{up});$$
$$\forall sc\in SC,\forall sw\in SW,\forall n\in N,\forall t\in T \tag{13}$$

$$\left|\Delta P_{sc,sw,n,t}^{hvac}\right|\le\Delta P_n^{hvac\_max}:(\rho_{sc,sw,n,t});\forall sc\in SC,\forall sw\in SW,\forall n\in N,\forall t\in T \tag{14}$$

$$\left|\sum_{n=1}^{N}P_{sc,n,t}^{cr}+P_{0_{n,t}}^{hvac}+\Delta P_{sc,sw,n,t}^{hvac}-P_{sw,t}^{w}\right|\le\left|\sum_{n=1}^{N}P_{sc,n,t}^{cr}+P_{0_{n,t}}^{hvac}-P_{sw,t}^{w}\right|$$
$$:(\upsilon_{sc,sw,t}^{lo},\upsilon_{sc,sw,t}^{up});\forall sc\in SC,\forall sw\in SW,\forall t\in T \tag{15}$$

$$\sum_{t=1}^{T}\Delta P_{sc,sw,n,t}^{hvac}=0\ :(\varepsilon_{sc,sw,n,t});\ \forall sc\in SC,\forall sw\in SW,\forall n\in N \tag{16}$$

$$Q_n^{hvac-\min}\le Q_{sc,sw,n,t}^{hvac}\le Q_n^{hvac-max}:(\delta_{sc,sw,n,t}^{lo},\delta_{sc,sw,n,t}^{up});$$
$$\forall sc\in SC,\forall sw\in SW,\forall t\in T,\forall n\in N \tag{17}$$

The HVAC system in this paper is an electric storage space heating system with a high thermal storage capacity, which is suitable for shifting its demand. Thermal storage capacity is provided by a tandem of a storage tank and building masses where the demand flexibility, provided by the latter one, comes at the cost of indoor temperature variation. In this study, the two key reasons for choosing the HVAC system for contributing to the DR program are: 1) in countries such as Finland, the HVAC systems make up a significant portion of electricity power demand and so considerably affect the daily load demand, and 2) the customers' comfort level is maintained by defining a temperature bound for them while for the other appliances, it is hard to find a way for specifying their comfort level in a satisfactory bound. In order to consider the dynamics of the environmental temperature, this paper utilizes a two-capacity model for the house system [23], [24], see Fig. 1. In this model, two capacities for heat regarding the air, $C_a$, and buildings materials, $C_m$, are considered. The constraints related to the two-capacity HVAC model are presented in (6) to (17). The indoor ambient and mass temperatures are shown by (6) and (7), respectively. The storage tank illustrated in Fig. 1, can be charged when there is an excess of energy (in our case, when the wind generation is higher than the consumers' demand) to reserve the heat energy for later usage during the shortage of energy (when the wind generation is lower than the consumers' load). In this way, the storage tank, together with thermal inertia of the house, provides high flexibility in scheduling of the demand. Generally, the comfort level of the consumers is specified by their preferences for lower and upper bound compared to indoor temperatures set in (8). The amount of thermal energy stored in the tank at each time, based on the last time thermal energy and other variables and parameters, is presented in (9). The minimum and maximum allowable amount of energy in thermal storage are presented by (10). The thermal energy reduces by time, according to (11), due to the energy losses in the tank. Constraint (12) limits the minimum and maximum for HVAC power change. Constraint (13) ensures that the HVAC power will remain in the allowable bounds after power change. The boundary of the absolute value of HVAC power is guaranteed by (14). Constraint (15) is to assure that the new deviation between wind and power consumption obtained by the proposed method is always less than or equal to the previous deviation. Constraint (16) guarantees that the summation of power changes in the HVAC system for the operating horizon should be equal to zero. In this way, a fair assessment of the suggested approach is obtained. The thermal output power of the HVAC is presented in (17). The thermal parameters related to the HVAC system and buildings are provided in Table I and [25].

## III. Problem Formulation

Considering (4) for the upper level, and (5) to (17) for the lower-level, a nonlinear bilevel programming model results. The consumers at the lower-level act as the followers and the aggregator in the upper-level act as the leader. The exchange variables for the upper-level are $bonus_{n,t}$ and for lower-level $\Delta P_{n,t}^{hvac}$. Since the lower-level problem is linear, it is possible to recast the presented bilevel problem into a single-level nonlinear equivalent by using the strong duality theorem [26]. It should be mentioned that while in such reformulations the privacy remains questionable, it is a suitable method to avoid the iterative/heuristic-based approaches for solving bilevel programming problems [27].

### A. Formulation

The first step for the formulation of the problem is substituting the lower-level problem by the sets of primal feasibility constraints (6)-(17), dual feasibility constraints (21)-(38), and the strong duality condition (20). In this reformulation, (21)-(22), (23)-(24), (25)-(26), and (27)-(28) are the dual constraints associated to $\Delta P_{n,t}^{hvac}$, $SoC_{n,t}^{hvac}$, $T_{n,t}^{a}$, $T_{n,t}^{m}$ variables, respectively. In addition, constraints (29)-(38) indicate the sign for the aforementioned dual variables. The strong duality condition guarantees that the primal and dual objective values must be equal. The single-level problem, including its bilinear terms, is presented as follows.

$$\begin{aligned}\min \sum_{sc=1}^{SC}\sum_{sw=1}^{SW}\pi_{sc}\pi_{sw}\Bigg(&\sum_{t=1}^{T}\left|\sum_{n=1}^{N}P_{sc,n,t}^{cr}+P_{0_{n,t}}^{hvac}+\Delta P_{sc,sw,n,t}^{hvac}-P_{sw,t}^{w}\right|\\&+w\sum_{t=1}^{T}\sum_{n=1}^{N}\left|\Delta P_{sc,sw,n,t}^{hvac}\right|bonus_{sc,sw,n,t}\Bigg)\end{aligned} \tag{18}$$

$$\text{Constraints (6)-(17)} \tag{19}$$

$$\begin{aligned}&\sum_{sc=1}^{SC}\sum_{sw=1}^{SW}\pi_{sc}\pi_{sw}b\sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{y^+=1}^{Y^+}m_{y^+,n,t}^{+}\delta P_{y^+,sc,sw,n,t}^{hvac+}+\\&\sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{y^-=1}^{Y^-}m_{y^-,n,t}^{-}\delta P_{y^-,sc,sw,n,t}^{hvac-}+2\sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{y^+=1}^{Y^+}\sum_{y^-=1}^{Y^-}w_{y^+,y^-,sc,sw,n,t}=\\&\sum_{n=1}^{N}\sum_{t=1}^{T}\left(\begin{aligned}&\beta_{sc,sw,n,t}^{lo}(T_{n,t}^{set}-\frac{\theta}{2})+\beta_{sc,swn,t}^{up}(T_{n,t}^{set}+\frac{\theta}{2})+\\&\mu_{sc,sw,n,t}^{lo}SoC_{n,t}^{\min}+\mu_{,sc,sw,n,t}^{up}SoC_{n,t}^{\max}-\iota_{sc,sw,n,t}^{lo}\Delta P_{n}^{hvac\_\max}\\&+\iota_{sc,sw,n,t}^{up}\Delta P_{n}^{hvac\_\max}+\nu_{sc,sw,n,t}^{up}(P_{n}^{hvac\_\max}-P_{0_{n,t}}^{hvac})\\&+\rho_{sc,sw,n,t}.\Delta P_{n}^{hvac\_\max}-\delta_{sc,sw,n,t}^{lo}Q_{n}^{hvac\_\max}\\&+\delta_{sc,sw,n,t}^{up}Q_{n}^{hvac\_\max}\end{aligned}\right)\\&+\sum_{n=1}^{N}\lambda_{sc,sw,n,1}\frac{T_{sc,sw,n,0}^{a}+[H_{n}^{m}T_{sc,sw,n,0}^{m}+H_{n}^{e}T_{1}^{e}+H_{n}^{g}T_{1}^{g}+H_{n}^{x}T^{x}]/C_{n}^{a}}{1+[H_{n}^{m}+H_{n}^{e}+H_{n}^{g}+H_{n}^{x}]/C_{n}^{a}}\\&+\sum_{n=1}^{N}\sum_{t=2}^{T}\lambda_{sc,sw,n,t}\frac{\frac{1}{C_{n}^{a}}[H_{n}^{e}T_{t}^{e}+H_{n}^{g}T_{t}^{g}+H_{n}^{x}T^{x}]}{1+\frac{1}{C_{n}^{a}}[H_{n}^{m}+H_{n}^{e}+H_{n}^{g}+H_{n}^{x}]}+\sum_{n=1}^{N}\varphi_{sc,sw,n,1}.\\&\frac{T_{sc,sw,n,0}^{m}+\frac{1}{C_{n}^{m}}[H_{n}^{m}T_{sc,sw,n,0}^{a}+H_{n}^{y}T_{1}^{e}]}{1+\frac{1}{C_{n}^{m}}[H_{n}^{m}+H_{n}^{y}]}+\sum_{n=1}^{N}\sum_{t=2}^{T}\varphi_{sc,sw,n,t}\frac{\frac{1}{C_{n}^{m}}[H_{n}^{y}T_{t}^{e}]}{1+\frac{1}{C_{n}^{m}}[H_{n}^{m}+H_{n}^{y}]}\\&+\sum_{n=1}^{N}\alpha_{sc,sw,n,1}(SoC_{n,0}+\eta^{c}P_{0_{n,0}}^{hvac}-\xi_{n,0})+\sum_{n=1}^{N}\sum_{t=2}^{T}\alpha_{n,t}\eta^{c}P_{0_{n,0}}^{hvac}\end{aligned} \tag{20}$$

$$\begin{aligned}&-\eta^{c}\alpha_{n,t}+\iota_{n,t}^{lo}+\iota_{n,t}^{up}+\nu_{n,t}^{lo}+\nu_{n,t}^{up}+\rho_{n,t}+\varepsilon_{n,t}+\upsilon_{t}^{lo}+\upsilon_{t}^{up}\\&=bonus_{n,t};\forall t\in T,\forall n\in N\end{aligned} \tag{21}$$

$$\begin{aligned}&\eta^{c}\alpha_{n,t}-\iota_{n,t}^{lo}-\iota_{n,t}^{up}-\nu_{n,t}^{lo}-\nu_{n,t}^{up}+\rho_{n,t}-\varepsilon_{n,t}-\upsilon_{t}^{lo}-\upsilon_{t}^{up}\\&=bonus_{n,t};\forall t\in T,\forall n\in N\end{aligned} \tag{22}$$

$$\alpha_{n,t}-\alpha_{n,t+1}+\mu_{n,t}^{lo}+\mu_{n,t}^{up}-\eta_{n}\sigma_{n,t}=0;\forall t=1...T-1,\forall n\in N \tag{23}$$

TABLE II
COMPUTATIONAL COMPLEXITY

| | Size | Order of Complexity |
|---|---|---|
| # of positive continuous variables | $11SC.SW.N.T + SC.SW.y^{+}.N.T + SC.SW.y^{-}.N.T + SC.SW.T$ | $11SC.SW.N.T + SC.SW.N.T + SC.SW.N.T + SC.SW.T$ |
| # of negative continuous variables | $6SC.SW.N.T$ | $6SC.SW.N.T$ |
| # of free continuous variables | $11SC.SW.N.T + SC.SW.N.T.y^{+}.y^{-}$ | $11SC.SW.N.T + SC.SW.N.T$ |
| # of equality constraints | $2SC.SW.N.T.y^{+}.y^{-} + 2N.T+.SC.SW.T + 23SC.SW.N.T$ | $2SC.SW.N.T + 2N.T+.SC.SW.T + 23SC.SW.N.T$ |
| # of inequality constraints | $4SC.SW.T + 24SC.SW.N.T + SC.SW.y^{+}.N.T + SC.SW.y^{-}.N.T + SC.SW.N.T.y^{+}.y^{-}$ | $4SC.SW.T + 24SC.SW.N.T + SC.SW.N.T + SC.SW.N.T + SC.SW.N.T$ |

$$\alpha_{n,T} + \mu^{lo}_{n,T} + \mu^{up}_{n,T} - \eta_n \sigma_{n,T} = 0 ;\forall n \in N \tag{24}$$

$$\lambda_{n,t} - \frac{1}{1+[H^m_n + H^e_n + H^g_n + H^x_n]\big/ c^a_n}\lambda_{n,t+1} + \beta^{lo}_{n,t} + \beta^{up}_{n,t} - \frac{H^m_n \big/ c^m_n}{1+(H^m_n + H^y_n)\big/ c^m_n}\varphi_{n,t+1} + = 0 ;\forall t = 1\ldots T-1, \forall n \in N \tag{25}$$

$$\lambda_{n,T} + \beta^{lo}_{n,T} + \beta^{up}_{n,T} = 0 ;\forall n \in N \tag{26}$$

$$\frac{-\lambda_{n,t}\big/ c^a_n}{1+[H^m_n + H^e_n + H^g_n + H^x_n]\big/ c^a_n} + \frac{1}{\eta^d}\alpha_{n,t} + \delta^{lo}_{n,t} + \delta^{up}_{n,t} = 0 ;\forall t \in T, \forall n \in N \tag{27}$$

$$-\frac{H^m_n\big/ c^a_n}{1+[H^m_n + H^e_n + H^g_n + H^x_n]\big/ c^a_n}\lambda_{n,t+1} + \varphi_{n,t} - \frac{1}{1+(H^m_n + H^y_n)\big/ c^m_n}\varphi_{n,t+1} = 0 ;\forall t = 1\ldots T-1, \forall n \in N \tag{28}$$

$$\varphi_{n,T} = 0;\ \forall n \in N \tag{29}$$

$$\alpha_{n,t+1} + \sigma_{n,t} = 0; \forall t = 1\ldots T, \forall n \in N \tag{30}$$

$$\sigma_{n,T} = 0 \ ;\forall n \in N \tag{31}$$

$$\beta^{lo}_{n,t} \le 0,\ \beta^{up}_{n,t} \ge 0; \forall t \in T, \forall n \in N \tag{32}$$

$$\mu^{lo}_{n,t} \le 0,\ \mu^{up}_{n,t} \ge 0; \forall t \in T, \forall n \in N \tag{33}$$

$$\iota^{lo}_{n,t} \le 0,\ \iota^{up}_{n,t} \ge 0; \forall t \in T, \forall n \in N \tag{34}$$

$$\nu^{lo}_{n,t} \le 0,\ \nu^{up}_{n,t} \ge 0; \forall t \in T, \forall n \in N \tag{35}$$

$$\delta^{lo}_{n,t} \le 0,\ \delta^{up}_{n,t} \ge 0; \forall t \in T, \forall n \in N \tag{36}$$

$$\rho_{n,t} \ge 0; \forall t \in T, \forall n \in N \tag{37}$$

$$\upsilon^{lo}_{t} \le 0,\ \upsilon^{up}_{t} \ge 0; \forall t \in T \tag{38}$$

As can be seen, there are some nonlinear terms in (18) and (19). The nonlinearity itself is not a major issue in the optimization problem, however, the non-convexities make a severe obstacle in finding the global solution. In order to address this issue, some proper linearization techniques are applied to linearize the absolute value function and also the quadratic term existed in the objective function. The resulted linear single-level problem is presented in (41) to (56).

The first term in (18), which includes an absolute value, is replaced with the linearized terms in (39), and it adds constraint (42) to the problem. For linearization of the square terms in (39), it is transformed into (40) where (43) to (50) are included for this reason. Interested readers may refer to [28] for more information. A similar linearization is performed for the left-hand side of (20). In addition, there is a multiplication of two continuous variables in (40) that is substituted with linearized form in (41) via the McCormick envelopes (51) to (54).

$$\min\left( w\sum_{t=1}^{T} f_t + \sum_{t=1}^{T}\sum_{n=1}^{N} b(\Delta P^{hvac+}_{n,t} + \Delta P^{hvac-}_{n,t})^2 \right) = \min \sum_{sc=1}^{SC}\sum_{sw=1}^{SW} w\pi_{sc}\pi_{sw}\left( \sum_{t=1}^{T} f_{sc,sw,t} + b\sum_{t=1}^{T}\sum_{n=1}^{N}\left(\Delta P^{hvac+}_{sc,sw,n,t} + \Delta P^{hvac-}_{sc,sw,n,t}\right)^2 \right) \tag{39}$$

$$\min \sum_{sc=1}^{SC}\sum_{sw=1}^{SW} w\pi_{sc}\pi_{sw}\left( \sum_{t=1}^{T} f_{sc,sw,t} + b\sum_{t=1}^{T}\sum_{n=1}^{N}\left( \sum_{y^+=1}^{Y^+} m^{+}_{y^+,n,t}\,\delta P^{hvac+}_{y^+,sc,sw,n,t} + \sum_{y^-=1}^{Y^-} m^{-}_{y^-,n,t}\,\delta P^{hvac-}_{y^-,sc,sw,n,t} + 2\sum_{y^+=1}^{Y^+}\sum_{y^-=1}^{Y^-}\delta P^{hvac+}_{y^+,sc,sw,n,t}\,\delta P^{hvac-}_{y^-,sc,sw,n,t} \right)\right) \tag{40}$$

$$\min w\sum_{sc=1}^{SC}\sum_{sw=1}^{SW}\pi_{sc}\pi_{sw}\left( \sum_{t=1}^{T} f_{sc,sw,t} + b\sum_{t=1}^{T}\sum_{n=1}^{N}\left( \sum_{y^+=1}^{Y^+} m^{+}_{y^+,n,t}\,\delta P^{hvac+}_{y^+,sc,sw,n,t} + \sum_{y^-=1}^{Y^-} m^{-}_{y^-,n,t}\,\delta P^{hvac-}_{y^-,sc,sw,n,t} + 2\sum_{y^+=1}^{Y^+}\sum_{y^-=1}^{Y^-} w_{y^+,y^-,sc,sw,n,t} \right)\right) \tag{41}$$

$$-f_t \le \sum_{n=1}^{N} P^{cr}_{n,t} + P^{hvac}_{0_{n,t}} + (\Delta P^{hvac+}_{n,t} - \Delta P^{hvac-}_{n,t}) - P^{w}_{t} \le f_t; \forall t \in T \tag{42}$$

$$0 \le \delta P^{hvac+}_{y^+,n,t} \le \Delta P^{hvac\_max}_{n} \Big/ Y^{+} ; \forall y \in Y, \forall n \in N, \forall t \in T \tag{43}$$

$$0 \le \delta P^{hvac-}_{y^-,n,t} \le \Delta P^{hvac\_max}_{n} \Big/ Y^{-} ; \forall y \in Y, \forall n \in N, \forall t \in T \tag{44}$$

$$m^{+}_{y^+,n,t} = (2y^{+} - 1)\Delta P^{hvac\_max}_{n} \Big/ Y^{+} ; \forall y^{+} \in Y^{+}, \forall n \in N, \forall t \in T \tag{45}$$

$$m^{-}_{y^-,n,t} = (2y^{-} - 1)\Delta P^{hvac\_max}_{n} \Big/ Y^{-} ; \forall y^{-} \in Y^{-}, \forall n \in N, \forall t \in T \tag{46}$$

$$\Delta P^{hvac+}_{n,t} = \sum_{y^+=1}^{Y^+} \delta P^{hvac+}_{y^+,n,t} \ ; \forall n \in N, \forall t \in T \tag{47}$$

$$\Delta P^{hvac-}_{n,t} = \sum_{y^-=1}^{Y^-} \delta P^{hvac-}_{y^-,n,t} \ ; \forall n \in N, \forall t \in T \tag{48}$$

$$(\Delta P^{hvac+}_{n,t})^2 = \sum_{y^+=1}^{Y^+} m^{+}_{y^+,n,t}\,\delta P^{hvac+}_{y^+,n,t} \ ; \forall n \in N, \forall t \in T \tag{49}$$

$$(\Delta P^{hvac-}_{n,t})^2 = \sum_{y^-=1}^{Y^-} m^{-}_{y^-,n,t}\,\delta P^{hvac-}_{y^-,n,t} \ ; \forall n \in N, \forall t \in T \tag{50}$$

$$w_{y^+,y^-,n,t} \ge 0;\ \ \forall y^{+} \in Y^{+}, \forall y^{-} \in Y^{-}, \forall n \in N, \forall t \in T \tag{51}$$

$$w_{y^+,y^-,n,t} \ge \Delta P^{hvac\_max}_{n}\,\delta P^{hvac-}_{y^-,n,t} \Big/ Y^{-} + \Delta P^{hvac\_max}_{n}\,\delta P^{hvac+}_{y^+,n,t} \Big/ Y^{+} - \left(\Delta P^{hvac\_max}_{n}\right)^2 \Big/ Y^{+}Y^{-};\ \ \forall y^{+} \in Y^{+}, \forall y^{-} \in Y^{-}, \forall n \in N, \forall t \in T \tag{52}$$

$$w_{y^+,y^-,n,t} \le \Delta P^{hvac\_max}_{n}\,\delta P^{hvac+}_{y^+,n,t} \Big/ Y^{-}; \forall y^{+} \in Y^{+}, \forall y^{-} \in Y^{-}, \forall n \in N, \forall t \in T \tag{53}$$

$$w_{y^+,y^-,n,t} \le \Delta P^{hvac\_max}_{n}\,\delta P^{hvac-}_{y^+,n,t} \Big/ Y^{+}; \forall y^{+} \in Y^{+}, \forall y^{-} \in Y^{-}, \forall n \in N, \forall t \in T \tag{54}$$

Constraints (6)-(17) (55)

Constraints (21)-(38) (56)

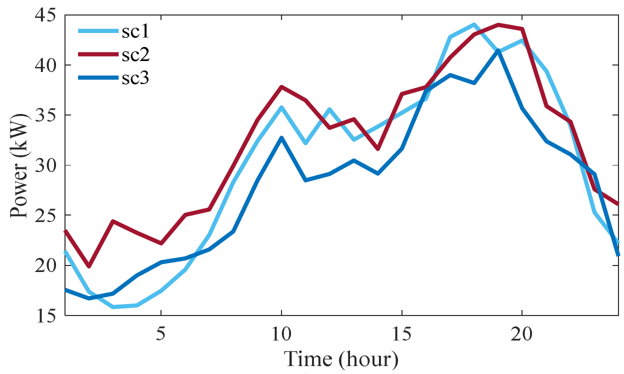

Fig. 2. Scenarios for non-HVAC loads

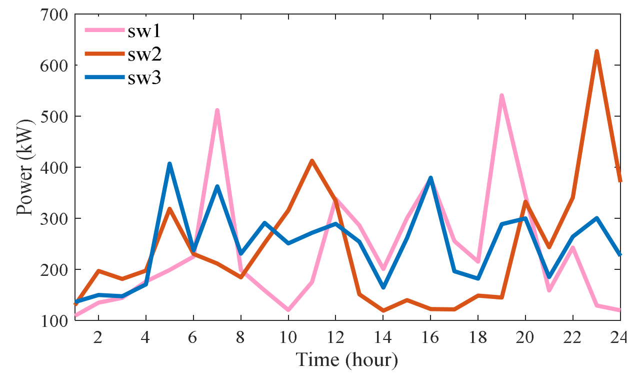

Fig. 3. Scenarios for wind farm

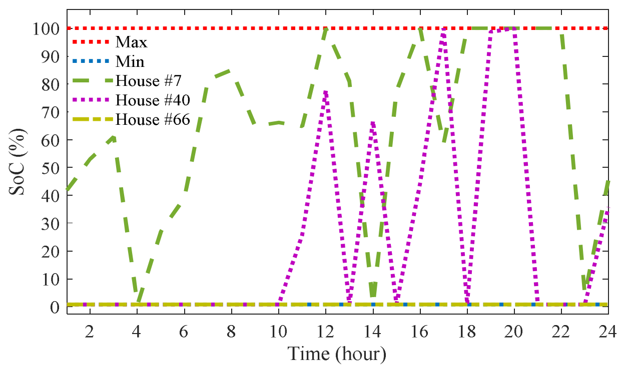

Fig. 4. SoC of HVAC system (scenario 1)

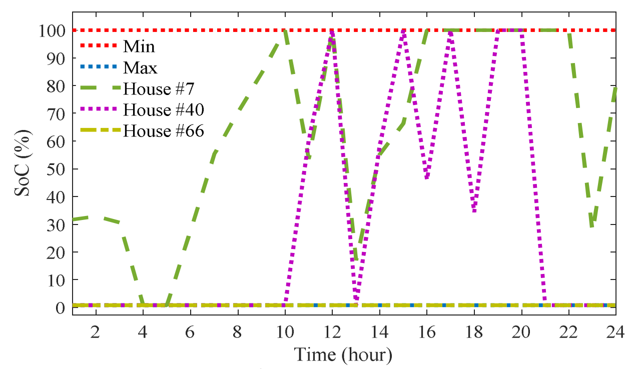

Fig. 5. SoC of HVAC system (scenario 6)

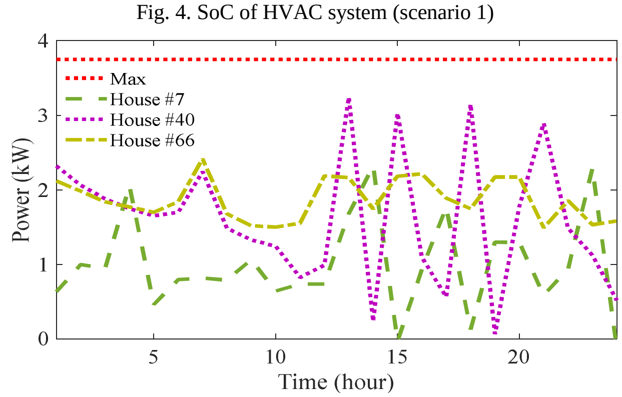

Fig. 6. Thermal output power (scenario 1)

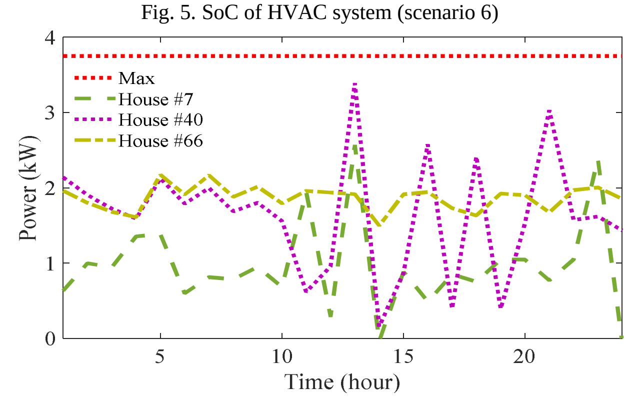

Fig. 7. Thermal output power (scenario 6)

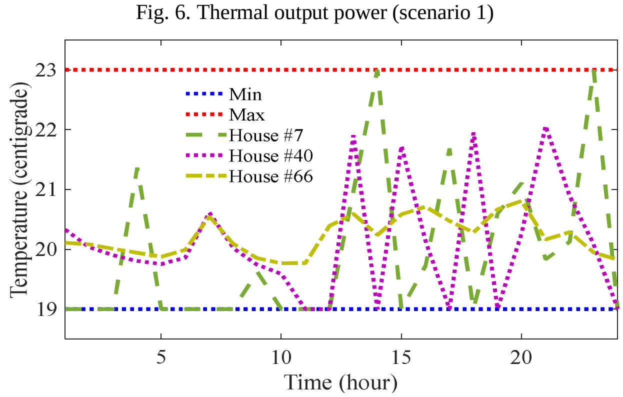

Fig. 8. Indoor temperature (scenario 1)

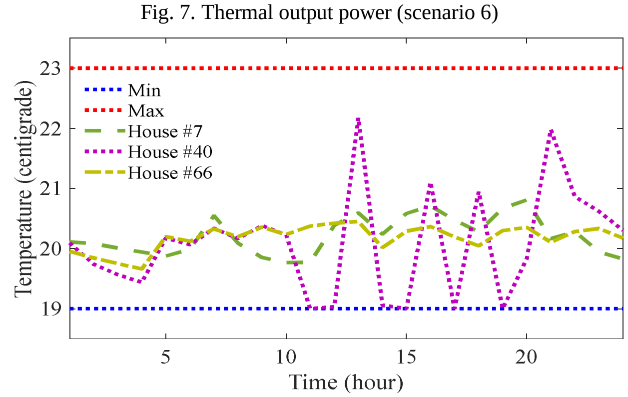

Fig. 9. Indoor temperature (scenario 6)

## B. *Computational issues*

Table II shows the computational complexity of the proposed strong duality based linear programming. The second column shows the corresponding size of the first column and the third column also indicates the order of complexity for the large scale systems. The order of complexity of the aforementioned problem increases in proportion to SC, SW, N, T. Note that the number of $y^+$ and $y^-$ does not affect the problem size for the large scale systems, since the number of segments for linearization is assumed to be fixed.

## IV. Simulation Results

In this section, we considered two different time resolutions for simulation, namely one-hour and five-minute time resolution. The proposed models have been implemented on an

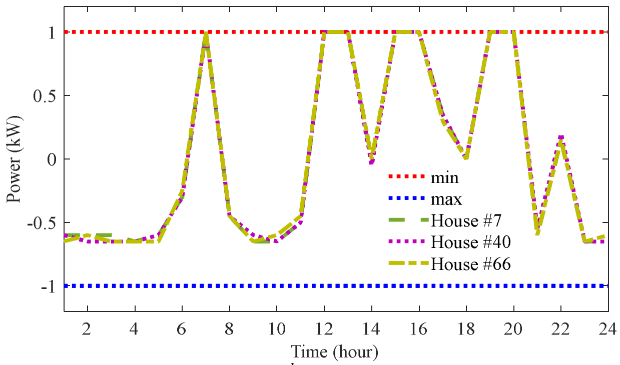


Fig. 10. $\Delta P^{hvac}$ (scenario 1)

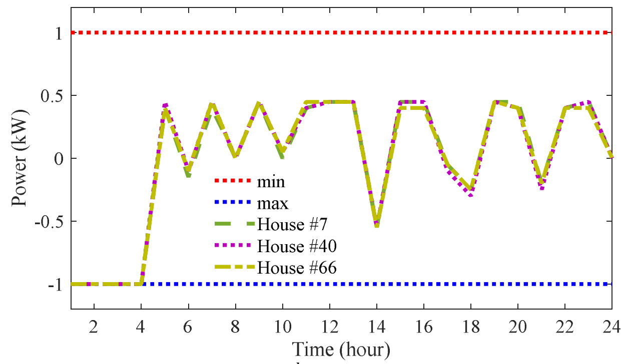


Fig. 11. $\Delta P^{hvac}$ (scenario 6)

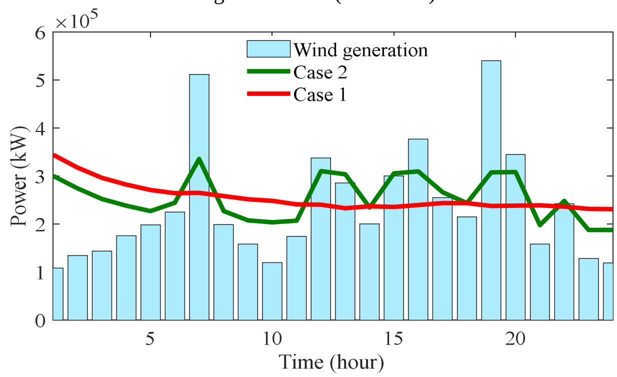


Fig. 12. Generated wind power and the total load of all houses (scenario 1)

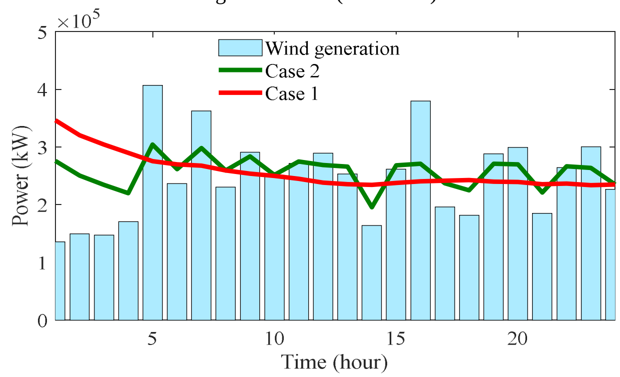


Fig. 13. Generated wind power and the total load of all houses (scenario 6)

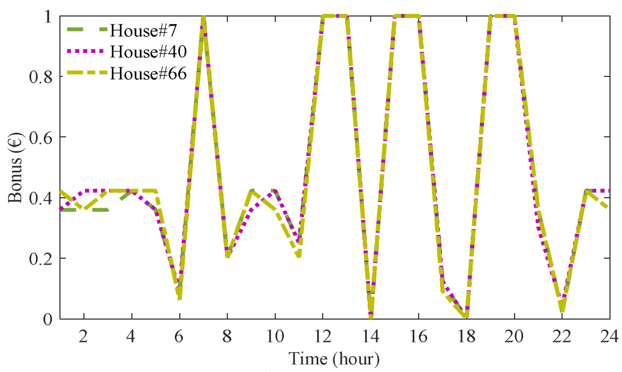


Fig. 14. Bonus for consumers (scenario 1)

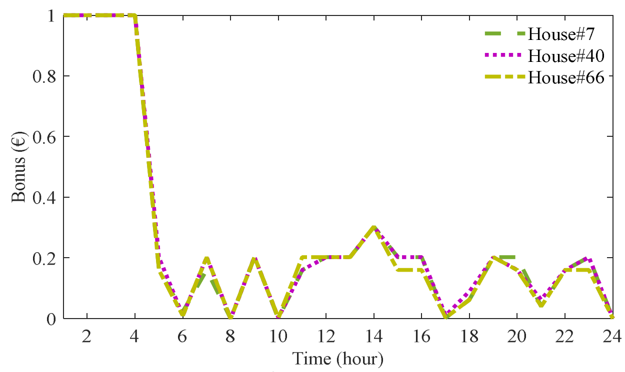


Fig. 15. Bonus for consumers (scenario 6)

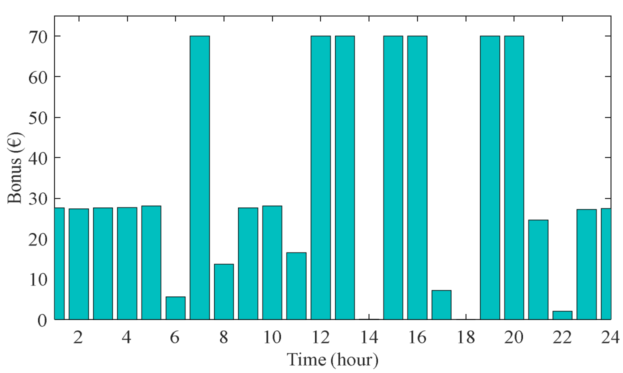


Fig. 16. Total bonus received by all consumers (scenario 1)

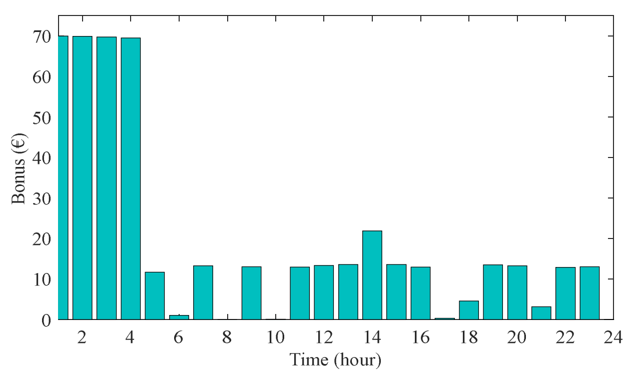


Fig. 17. Total bonus received by all consumers (scenario 6)

HP Z240 Tower Workstation with eight Intel Xeon E3-1230 v5 processors at 3.4 GHz and 16 GB of RAM using CPLEX 12.8 [29] under GAMS 25.1.2 [30].

### *A. One-hour time resolution*

In order to implement the proposed approach, a case study with 24 hours and a 1-hour resolution is considered in this section. The time 1 (hour 1) in all figures indicates 1 a.m. and time 24 shows 12 p.m. A simulation is conducted in a residential area comprising 70 houses with different parameters (see Table III). The temperature is shown in Table IV. Each home is supposed to have a critical load that inevitably must be

TABLE III
NUMBER OF HOUSES WITH DIFFERENT SQUARE METERS

| Area (Square Meters) | 90 | 100 | 110 | 120 | 130 | 140 | 150 | 160 | 170 | 180 | 190 | 200 | 210 | 220 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Number | 5 | 5 | 5 | 6 | 6 | 6 | 5 | 5 | 5 | 5 | 5 | 4 | 4 | 4 |

TABLE IV
OUTDOOR TEMPERATURE (CENTIGRADE)

| Hour | Temperature | Hour | Temperature |
|---|---|---|---|
| 1 | -3.1 | 13 | -2.6 |
| 2 | -2.5 | 14 | -4.1 |
| 3 | -1.7 | 15 | -4.0 |
| 4 | -2.2 | 16 | -5.2 |
| 5 | -2.2 | 17 | -4.9 |
| 6 | -2.9 | 18 | -4.8 |
| 7 | -4.7 | 19 | -4.1 |
| 8 | -3.2 | 20 | -4.3 |
| 9 | -2.2 | 21 | -5.7 |
| 10 | -2.0 | 22 | -6.4 |
| 11 | -2.5 | 23 | -7.4 |
| 12 | -2.6 | 24 | -8.0 |

TABLE V
DEVIATION BETWEEN LOAD CONSUMPTION AND WIND POWER

| Scenario | Total deviation without DR (kW) | Total deviation with DR (kW) |
|---|---|---|
| 1 | 2520.506 | 1552.600 |
| 2 | 2539.462 | 1463.758 |
| 3 | 1683.293 | 996.802 |
| 4 | 2552.736 | 1589.640 |
| 5 | 2560.769 | 1491.701 |
| 6 | 1680.453 | 1004.896 |
| 7 | 2519.849 | 1698.998 |
| 8 | 2542.322 | 1445.588 |
| 9 | 1682.960 | 979.624 |

satisfied. On the other hand, the HVAC system is considered as a flexible load, capable of changing its power based on the associated constraints in (6)-(17). In order to verify the effectiveness of the proposed approach, two separate case studies are taken into account. Case 1 aims at defining a benchmark, and to do so, it is assumed that there is no control over the HVAC systems for participating in the DR program. The temperature of the house is kept at 21 ℃. In this way, the $P_{o,n,t}^{hvac}$, which is the HVAC power for each house in each hour, is calculated.

In the second case, the HVAC system is activated for the proposed DR program by regulating its power (plus-minus 1000 Watt at maximum for each house and each hour). A plus-minus two degrees deviation from the houses' indoor temperature set points in Case 1 has been considered for Case 2. Consequently, the $\Delta P_{sc,sw,n,t}^{hvac}$ (power deviation from the calculated benchmark in the first case), is obtained. It is worth mentioning that each consumer can choose their preferences for the indoor temperature and its deadband (higher and lower than the average temperature). As depicted in Fig. 2 and Fig. 3, three scenarios for non-HVAC load and three scenarios for wind power are considered, which comprise nine scenarios overall. In order to validate the results, two scenarios have been chosen and the simulation results are illustrated for them: scenario1 (the combination of sc1 of non-HVAC load and sw1 of wind power) and scenario 6 (the combination of sc3 of non-HVAC load and sw2 of wind power).

In Figs. 4 and 5, the state of charge (SoC) for three selected houses, including #7, #40, and #66, and for two scenarios are depicted. These three houses are selected out of 70 as a representative for different scales of houses. The areas of house #7, #40, and #66 are 100, 160, and 210 square meters, respectively. It is shown in Fig. 4 and Fig. 5 that the SoC level has remained between the minimum and maximum allowable amounts. SoC value is the energy which is stored and released in and from the thermal storage (such as hot water tank) in order to facilitate shifting the HVAC system's demand to other appropriate hours. Figs. 6 and 7 illustrate the thermal output power of the HVAC systems for the houses mentioned above, while Figs. 8 and 9 show their indoor temperature. Increasing and decreasing the thermal output power means rising and dropping in the indoor temperature. This thermal energy can come from heat storage or directly from the electric power, which transforms into heating energy. The deadband temperature is considered plus-minus 2 degrees from the 21 ℃, which was set as our benchmark. It can be seen in Figs. 8 and 9 that the temperature is kept within the defined zone in both scenarios. It indicates that the comfort level of all houses is appropriately maintained.

It is noteworthy to mention that there exists a correlation between the fluctuations of the curves depicted in Figs. 4, 6, and 10. Any increase in $\Delta P_{n,t}^{hvac}$ in Fig. 10, causes a rise either in the thermal output power in Fig. 6 or the SoC of the storage tank in Fig. 4. It means that the increase in the electrical consumption of the HVAC system either results in thermal output power or stores in the storage tank. This can be seen between hours 6 and 8 where there is a peak in $\Delta P_{n,t}^{hvac}$ in Fig. 10 that results in an increase in the thermal output power of house # 40 and #66 in Fig. 6, while for house #7 in Fig. 4, the SoC is increased. From Figs. 6 to 9, it can be realized that the local maximums in the thermal output power profile stand for the states in which the indoor temperature reaches its local maximum. For example, for house #66 in scenario 1, in hours 7, 13, 15, 18, and 21, the indoor temperature reaches to 20.6, 21.8, 21.6, 21.8, and 22, respectively. Furthermore, when the output thermal power is at its minimum, for instance, for house #40, in hours 11, 12, 14, 17, 19 and 24, the indoor temperature is at its minimum point, which is 19 ℃. In Figs. 10 and 11, the power change of the HVAC system for Scenarios 1 and 6 is illustrated. When the proposed DR program is activated, the HVAC power is changed to positively react to the aggregator request, which is minimizing the mismatch between the wind power and the load demand, while making the most benefit of the receiving bonus. There are four peaks in Figs. 10 and 11, which shows the compensation of HVAC demand for high wind-generated power on those hours. The forecasted wind power production is depicted in Figs. 12 and 13. It can be seen that at the early hours when the wind power is at its minimum, the HVAC systems reduce their load power as much as possible for maximum matching. Moreover, by comparing Fig. 10 with Fig. 12 and also Fig. 11 with Fig. 13, it can be deduced that when there are excess amounts of power due to more wind power production than consumers' demand, the HVAC systems are using more power than the first case (benchmark). This fact is also inferred

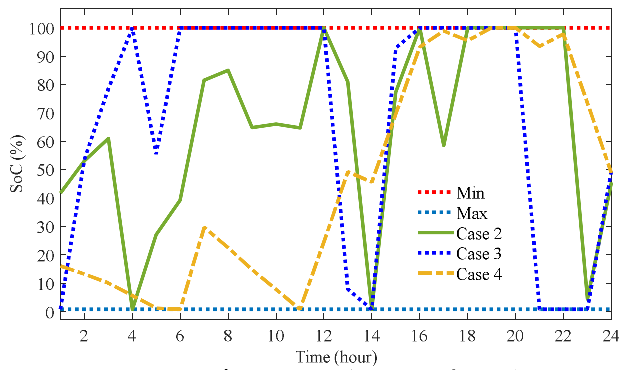

Fig. 18. SoC of HVAC system (scenario 1 & house#7)

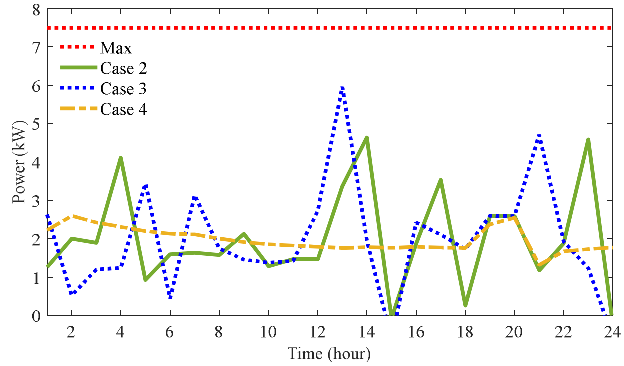

Fig. 19. Thermal output power (scenario 1 & house#7)

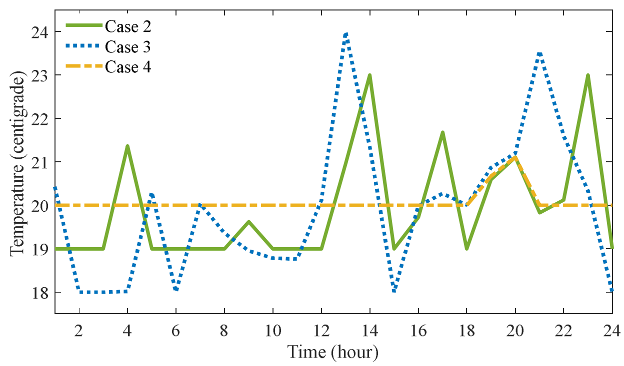

Fig. 20. Indoor temperature (scenario 1 & house#7)

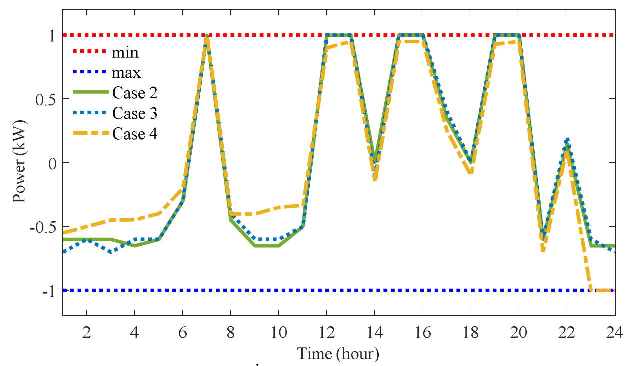

Fig. 21 . $\Delta P^{hvac}$ (scenario 1 & house#7))

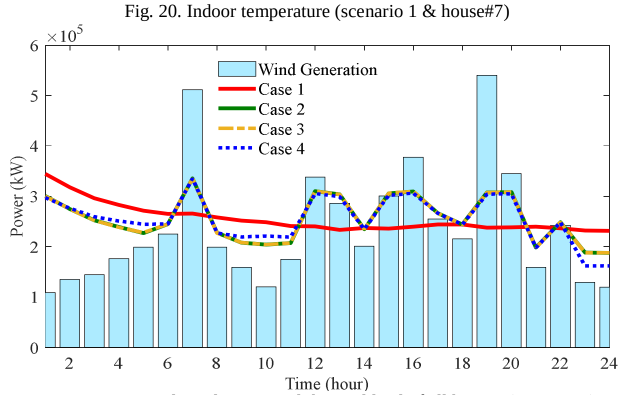

Fig. 22. Generated wind power and the total load of all houses (scenario 1)

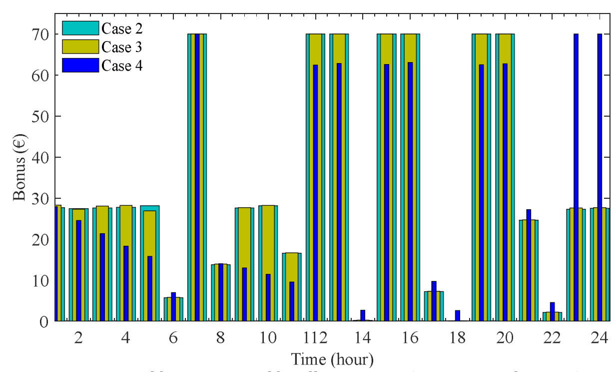

Fig. 23. Total bonus received by all consumers (scenario 1 & house#7)

in Figs. 6 and 7 where the thermal outputs of houses have increased in these hours according to the consumption of more energy. From Figs. 12 and 13, it can be evidently observed that the mismatch between residential load demand and wind power production using the proposed method has significantly decreased compared to the situation where the suggested approach is not activated.

In addition, the hourly deviation between wind power generation and residential load power consumption for all scenarios and for both cases (with and without the proposed DR program), is shown in Table V. The results of this table show that the total deviation has been decreased for all scenarios, which is a significant outcome of the proposed approach. This means that the consumers' load demand now tracks the produced wind power efficiently.

Figures 14 and 15 depict the amount of money that houses #7, #40, and #66 receive for their contribution in the DR program. This reward is quadratically proportional to the power change of HVAC (illustrated in Figs. 10 and 11). Finally, the total amount of bonus paid to all the consumers by the aggregator is demonstrated in Figs. 16 and 17. It can be easily recognized from these figures and Figs. 10 and 11 that when there is a big contribution of consumers for minimizing the mismatch between wind generation and load consumption, the aggregator has to compensate by giving more money to consumers. However, at some hours like 14 and 18 in scenarios 1 and 8 and hour 10 in scenario 2, the aggregator pays no bonus since there is no gap between wind power and demand. According to the abovementioned simulation results, it can be noticed that using the presented Stackelberg game scheme for incentivizing the consumers for participating in the DR program has been noticeably successful. Because in this way, both players in the game, i.e., the aggregator and consumers, are satisfied with the results. Not only has the imbalance between the generated power and consumption load reduced significantly, which is a merit for the aggregator, but the consumers receive a fair bonus for their contribution as well.

With the purpose of considering other cases, plus-minus 3 and plus-minus 1 degree from the 21 ℃ has been considered in case 3 and case 4, respectively. Figs. 18 to 22 depict the

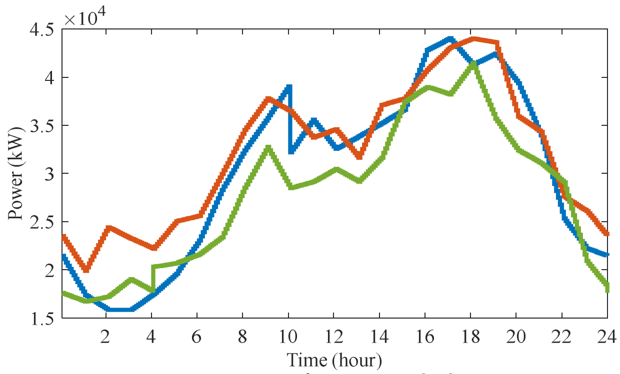

Fig. 24. Scenarios for non-HVAC loads

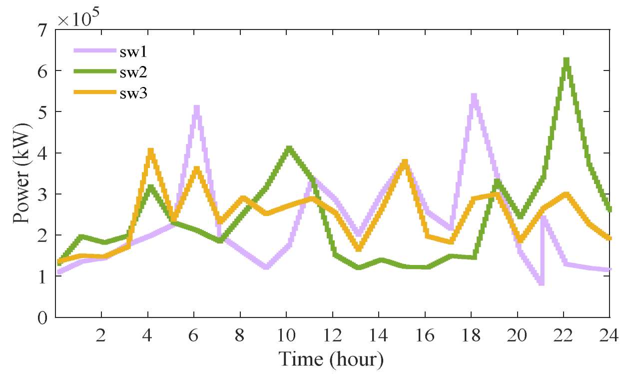

Fig. 25. Scenarios for wind power

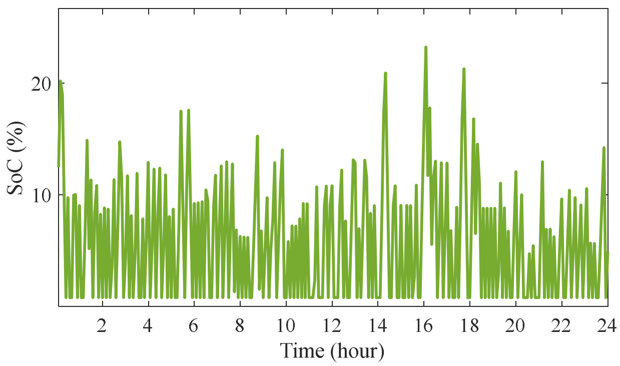

Fig. 26. SoC of HVAC system (scenario 1 & house #10)

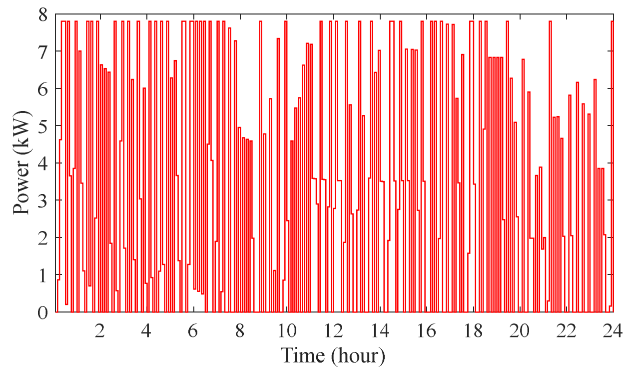

Fig. 27. Thermal output power (scenario 1 & house #10)

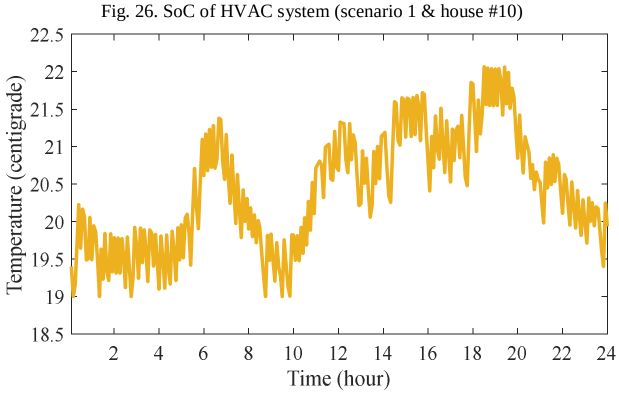

Fig. 28. Indoor temperature (scenario 1 & house #10)

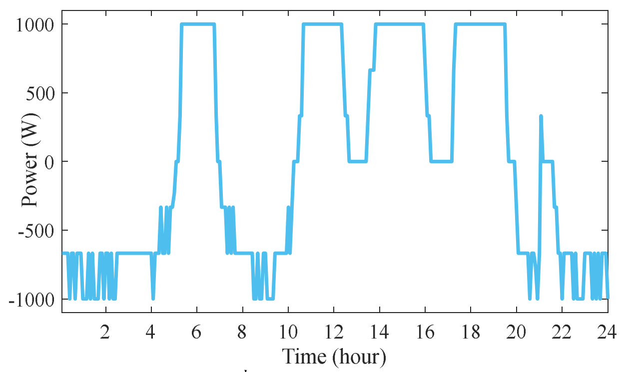

Fig. 29 . $\Delta P^{hvac}$ (scenario 1 & house #10))

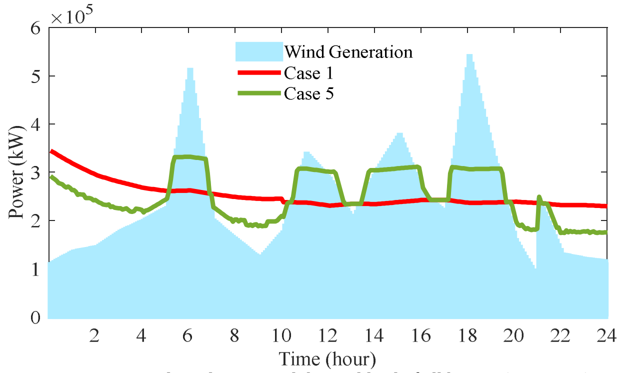

Fig. 30. Generated wind power and the total load of all houses (scenario 1)

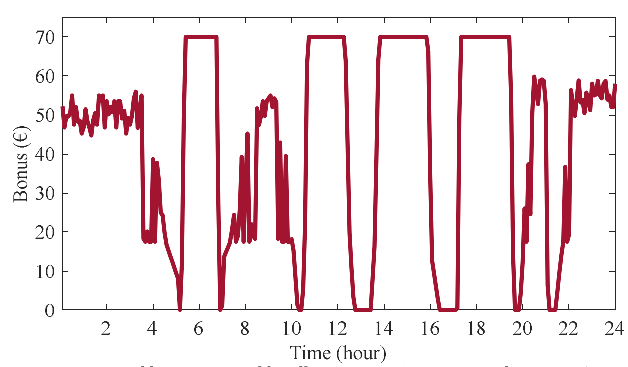

Fig. 31. Total bonus received by all consumers (scenario 1 & house #10 )

simulation results for the house 7 and scenario 1, which are selected randomly. In Figs. 18 and 19, the SoC of the heat tank and thermal output power are shown, respectively. According to Fig. 19, the thermal power for Case 2 is less than Case 3 but greater than Case 4. This is due to the variation of indoor temperature which is allowed for different cases and is demonstrated in Fig. 20. In Fig. 21, the HVAC system power variation is illustrated for the different three cases. Regarding Figs. 21, 22 and 23, it is clear that Case 2 is not that much different from Case 3, but it is better than Case 4. Because, as it is shown in Fig. 22, the gap between wind power and consumers' demand in Case 2 is less than Case 4 except in hour 23 and 24, but there is a negligible difference between Case 2 and Case 3. This fact is also understandable from Fig. 23, which shows the total bonus received by the consumers. The bonuses giving by the aggregator to the consumers is approaximately the same for Case 2 and Case 3 but different from Case 4. These results show that the HVAC system is using its maximum capacity for contributing to the demand response with plus-minus 2-degree deviation from the setpoint of indoor temperature while it is allowed to change its power up to 1000 watts.

### *B. Five-minutes time resolution*

Nowadays, the smart meters in the residential houses are interacting with aggregators or utility every one hour. However, in the near future, this interaction will be conducted every 15 minutes, or even in a shorter time interval. Consequently, with the aim of further discussion to examine the suggested method, Case 5 examines the proposed model even under higher critical time resolution, a 5-minutes time resolution has been considered in this section. The HVAC data is from Table I, except the maximum capacity of the HVAC system, which has considered 7800 kWh in this case. The temperature is shown in Table IV. We assumed that the temperatures change linearly between hours.

Figure 26 illustrates the SoC of heat storage during the 5 minutes resolution. Compared to the one-hour time resolution, the heat storage tank is not using its maximum capacity that implies a smaller capacity of the storage tank is needed for using the maximum potential of the HVAC system in DR. Fig. 27 shows the thermal output power of the HVAC. Variation in the thermal output power shows itself as changes in the indoor temperature. This thermal energy is supplied either by using electrical energy by HVAC systems, which are converted to heat power, or released from the heat storage tank. The variation limit for temperature is assumed plus-minus 2 degrees from the 21 °C. Figures 28 and 29 indicate the indoor temperature and changing of the HVAC system power, respectively. Looking at these figures, it is noticeable that increasing and decreasing the electrical usage of HVAC has resulted in the direct rise and fall in the temperature. This is different from the results obtained for the one-hour time resolution where the increased or decreased electrical usage was stored or released to or from heat storage. That is because of longer time step that existed for that simulation and caused to use of the heat storage tank fully compared to the 5 minutes time resolution, which is utilizing heat tank capacity with 25 percent at maximum. For example, regarding the peak in $\Delta P_{n,t}^{hvac}$ in hours 5:15-6:45, 10.15-12:05, 13:50-16:00, and 17:15-19:30 in Fig. 29, it has caused a temperature increase in Fig. 28. However, the temperature is kept within the defined zone during the whole time, which means the comfort level of all houses is properly preserved.

Finally, these variations in the HVAC power created a load profile that is following the wind generation better than the benchmark case. In Fig. 30, the wind power generation and also residential load power consumption for two cases (Case 1 and Case 5) are depicted. It can be realized that before hour 5 where the wind generation is not high, the HVAC systems decrease their load consumption to minimize the power difference between production and consumption. Moreover, when there are extra amounts of power due to the more wind power production for supplying consumers' demand, for instance, between 5-7 or 18-20, the HVAC systems are using more power to either store it in the heat storage or increase the indoor temperature. These actions by the HVAC system provide a smaller distance between generated wind power and the load demand of consumers.

On the other hand, the total amount of bonuses received by all the consumers and paid by the aggregator is portrayed in Fig. 31. It can be seen from this figure that the total bonus is dependent on the change of the HVAC power (see Fig. 29), which can be realized as the contribution of consumers for minimizing the imbalance between wind production and consumers' load.

## V. Conclusion

In this paper, a bonus-based DR program in a residential area consisting of 70 houses with different square meters has been considered. In order to take into account the interaction between the aggregator and consumers, a Stackelberg game model has been proposed. A case study with one leader and 70 followers is conducted. The aggregator side owns a wind power plant and tries to match the power consumption by all the houses to the wind-generated power. Hence, it provides bonuses to the consumer side for incentivizing them to adjust their load demand based on the forecasted wind power. This is possible by changing the HVAC system power in each house. The resulted problem, which is a bilevel programming model, is recast into a single level program using the strong duality theorem. This approach has been utilized to avoid the iterative process of finding the solution to the original bilevel program. From the simulation results and also Table V, it can be observed that the mismatch between the wind power generation and the residential load demand has remarkably decreased. According to this Table, the minimum and maximum improvement were in scenarios 7 and 8 with 32.58% and 43.14%, respectively. Taking the advantage of the Stackelberg game theory in this problem, not only does it lead to the optimal solution for the consumers (receiving a bonus based on their contributions, see Fig. 14-17), but it results in a reduced imbalance between wind power production and consumers' load profile as well. Considering Figs. 16 and 17, there are some hours such as 8 in scenarios 1 and 18 in scenario 6 where the consumers receive zero bonus due to their null contribution in the DR program. On the other hand, at hour 12 in scenario 1 and hour 1 in scenario 6 all consumers are participating in the DR program with their highest possible contribution (1000 Watts in our case) and they are receiving the maximum bonus which is equal to 1 €/hour for each of them and totally 70 € for all of them. The obtained results of the case with 5-minutes time resolution verifies the potential of the proposed method in handling the probable future scenarios. Future work will extend the proposed model to include other potential types of appliances such as electric vehicles, and considering the electric distribution network.

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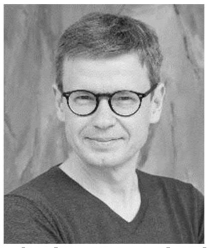

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