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Congestion management in active distribution networks through demand response implementation

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ABSTRACT

Despite the positive contributions of controllable electric loads such as electric vehicles (EV) and heat pumps (HP) in providing demand-side flexibility, uncoordinated operation of these loads may lead to congestions at distribution networks. This paper aims to propose a market-based mechanism to alleviate distribution network congestions through a centralized coordinated home energy management system (HEMS). In this model, the distribution system operator (DSO) implements dynamic tariffs (DT) and daily power-based network tariffs (DPT) to manage congestions induced by EVs and HPs. In this framework, the HP and EV loads are directly controlled by the retail electricity provider (REP). As DT and DPT price signals target the aggregated nodal demand, the individual uncoordinated HEMS models operating under these price signals are unable to effectively alleviate congestion. A large number of flexible residential customers with EV and HP loads are modeled in this paper, and the REP schedules the consumption based on the comfort preferences of the customers through HEMS. The effectiveness of the market-based concept in managing the congestion is demonstrated by using the IEEE 33-bus distribution system with 706 residential customers. The case study results show that considering both pricing systems can considerably mitigate the overloading occurrences in distribution lines, while applying DTs without considering DPTs may lead to severe overloading occurrences at some periods.

1. Introduction

Modern power systems are moving toward smart grids with a high penetration level of distributed generation (DG) units [1]. The number of controllable loads, such as electric vehicles (EV) and heat pumps (HP), is also constantly increasing in the grid [2]. Increased use of these potentially flexible loads is changing the daily electricity demand profile of consumers. Besides these technological changes in power grids, there has been a trend toward electricity market liberalization at wholesale and retail level. The liberalization reform, particularly at the retail level, encourages retail electricity providers (REP) to offer time variable rates to their clients.

This gradual transition in power systems is creating serious operational challenges for distribution systems [3]. Although the DG units help bypassing congestions in existing transmission grids [4], excessive power generation from DGs can cause congestion in distribution systems [5]. High demand due to EVs and HPs can also potentially cause overloading of the electricity lines. The distribution system operator (DSO) is confronted with congestion issues when a large number of these loads draws electricity from the grid simultaneously [6]. Uncoordinated operation of these flexible loads can cause unexpected congestions in the distribution system [5]. Real-time pricing (RTP) schemes offered by REPs in liberalized markets can also increase congestions in distribution systems by creating new peak demands in response to the time variable tariffs. The new peaks may cause overloading of lines and transformers [1].

Resolving the distribution grid congestion is considered as one of the main duties of DSOs [7]. In long-term planning, the DSO can reinforce the distribution grid according to the identified needs in order to avoid possible congestions in future [8]. It can increase the grid capacity through boosting the investments in the grid infrastructure [6]. The congestion management strategies in short-term are usually divided into three categories, which are distribution system reconfiguration (i.e., switch operation), direct load control and market-based mechanisms [1]. Market-based mechanisms compared to other two methods are more effective in the

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Nomenclature

Indices

t	Time intervals.
c	Consumers/houses
b	Buses.
v	EVs.
m	Operating modes of the HPs.

Variables

Payoff	Payoff of the REP during the scheduling horizon [€].
θ_c^{in}	Indoor temperature of house c [°C].
Q_c^{HP}	Heat flow of the HP of house c [W].
Q_c^{Loss}	Heat loss of house c [W].
p_c	Daily consumption schedule of house c [kWh].
p_b^{Peak}	Daily peak demand at bus b [kW]
$p_c^{Flexible}$	Flexible demand schedule of house c [kWh].
p_b	Aggregated demand at bus b [kWh]
$\lambda_b^{Congestion}$	DTs for congestion at bus b [€/kWh]
λ_b^{LMP}	Local marginal price (LMP) at bus b [€/kWh]
$P_v^{\mathrm{Ch/Dch}}$	Charging/discharging power of EV v [kW].
x_v^{Ch}	Charging status of EV v (1 if the EV is charging and 0 otherwise).
x_v^{Dch}	Discharging status of EV v (1 if the EV is discharging and 0 otherwise).
SoC_v	State of charge (SoC) of EV v in the end of time interval t [kWh].
f_c^{HP}	Total air mass of the HP [kg/h]
$f_{c,m}^{HP}$	Air mass flow at mode m [kg/h]
Ψ	Lagrangian function of DSO's problem.

Parameters

γ	Retail rates for the end-users [€/kWh].
λ^P	Predicted day-ahead market price [€/kWh].
λ_b^{DPT}	Daily power-based network tariff (DPT) at bus b [€/kWh].
θ^{out}	Outdoor forecasted temperature [°C].
μ_c	Total indoor air mass of house c [kg].
χ^{air}	Air heat capacity at standard conditions [J/kg °C].
Φ_c^{HP}	Air mass flow of the HP at house c [kg/h]
$\Phi_{c,m}^{HP}$	Maximum air mass flow at mode m [kg/h]
ρ_c^{HP}	Power per air mass flow of the HP [Wh/kg]
κ_c	Heat loss factor of house c [W/°C].
τ	Time interval duration [h].
p_c^{Firm}	Predicted firm load of house c [kWh].
$\eta_v^{\mathrm{Ch/Dch}}$	Charging/discharging efficiency of EV v.
SoC_v^{d}	Expected SoC of EV v at the departure time [kWh].
α_v	Arrival time of EV v.
β_v	Departure time of the EV v.
$SoC_v^{\mathrm{Min/Max}}$	Minimum/Maximum SoC level of EV v [kWh].
$\theta_c^{Low/Up}$	Lower/upper bound of the indoor temperature of house c [°C].
θ_c^{ref}	Reference indoor temperature of house c [°C].
$P_b^{Forecasted}$	Forecasted demand at bus b [kWh].
GSF_{k-b}	Generation shift factor to line k from bus b.
limit_k	Active power transmission limit of line k [kW].
$G_b^{Min/Max}$	Minimum/maximum generation output at bus b [kWh].

Sets

T	Time periods in the scheduling horizon.
K	Branches in the distribution network.
B	Buses in the distribution network.
T_v	$\mathrm{T}_v \subseteq \mathrm{T}$ is the set of periods in which EV v is connected to the grid; $\mathrm{T}_v = \{t \in \mathrm{T}: \alpha_v \le t \le \beta_v\}$.
T_h	$\mathrm{T}_h \subseteq \mathrm{T}$ is the set of periods that are within hour h.
C	All consumers served by the REP.
C_b	Consumers located at bus b.
Ω_{EV}	EVs operating under HEMS.
Ω_{EV}^c	EVs owned by consumer c.
M_{HP}^c	Modes of the HP owned by consumer c.

restructured electricity market environment. They can maximize the social welfare while causing least discomfort to customers and they can also enable the customers and the DGs to participate in the distribution network energy planning procedure [7]. Through market-based mechanisms, the DSO can harness the benefits of demand-side flexibility to face the challenges of the evolving electricity networks [9].

There are several technical and regulatory limitations for the DSO to directly control numerous flexible loads or to offer other types of demand response (DR) programs to electricity end-users [5,10]. REP is an ideal entity to offer DR programs to retail customers. They are the economic entities in the distribution network that purchase electricity in the wholesale market at volatile prices and sell to end-users at fixed rates [1]. They shield their clients against price variations in the wholesale market.

One of the risk management strategies of REPs is employing the demand-side resources. They can control the consumption of their clients' appliances to avoid more purchases from the market when the prices are high and in exchange offer more profitable contracts to their customers for their economic compensations [1]. REPs as commercial entities have a greater incentive for maximizing the payoff, compared to individual end-users. Therefore, implementing DR by them will lead to a higher elasticity of demand and more effective response to price signals [10]. In short-term consumption scheduling of the household appliances, the objective of the REP is to maximize its payoff [1]. This paper aims to develop a market-based mechanism for DSOs to alleviate congestions in distribution network through a coordinated home energy management system (HEMS) which is centrally controlled by REPs.

The concept of nodal pricing has been extended from transmission systems to distribution systems to reduce line losses and improve the voltage profile by rewarding the DGs [11] or to optimally allocate the DG units in the distribution network [12–14]. Nodal pricing was first used in distribution networks to handle the congestion problems in grids with high penetration of DG units [7].

This pricing mechanism was later used in some existing literature to address the congestion due to flexible demands in distribution networks [1,5,7,8,10,15,16]. A step-wise dynamic tariff (DT) scheme is developed by O'Connell et al. [10] to manage the congestion in distribution networks due to the EV demand. The DTs were calculated from the distribution locational marginal prices (LMP). In this decentralized control manner, the aggregators determine the energy plan of the EVs without taking the network constraints into consideration and the network constraint information is incorporated in the DTs. This method does not consider the inter-temporal characteristics of the EVs. Li et al. [15] also used distribution LMPs determined by the DSO as price signals for EV aggregators. The DSO determines the distribution LMPs by solving the social welfare optimization problem. A nonlinear optimization model was used to compute the prices. These models are only practically applicable when the DSO has access to the details of individual EVs [15,16]. To overcome this drawback in this paper, REPs are considered as an intermediary entity between the DSO and the consumers which access to the consumption data of the end-users and the details of individual EVs.

In the market-based mechanism developed by Liu et al. [1] to manage the distribution system congestions, household appliances with flexible demand such as EV and HP were selected as DR sources and the aggregators control their consumption based on distribution congestion prices. The distribution congestion prices are published by the DSO in advance. The objective of the aggregators was to maximize their total payoff.

Huang et al. [7] presented a quadratic programming model to alleviate the congestions in distribution networks with high penetration of flexible demand through introducing distribution LMPs. This paper proved that the distribution LMP concept is valid with the cost functions having quadratic terms reflecting the price sensitivity of the DGs. Moreover, the capability of this concept in addressing the congestion issue in distribution networks caused by diverse flexible load characteristics was proved.

Liu et al. [8] implemented the distribution LMP method via a chance constrained mixed-integer quadratic programming to manage congestions in distribution networks with high penetration of EVs. In this model, both DSO and the aggregators were involved in stochastic features of the EVs' driving pattern. Dealing with the stochastic features of EVs for DSO gets difficult in networks with high penetration of EVs and several aggregator players. A bi-level optimization model for day-ahead congestion management was developed by Ni et al. [5]. Uncertainties of the DG units and market prices were considered in a robust optimization model.

REPs can deploy the demand-side flexibility through coordinating the HEMSs of the end-users and applying the DTs in scheduling the consumption. HEMS can be implemented either centralized or decentralized [17]. In the decentralized HEMS models, consumption scheduling and control is done locally at the end-users' points. Fotouhi Ghazvini et al. [18] proposed a decentralized HEMS model which schedules the household consumption based on the price signals received from the REP. The customers in decentralized HEMS models minimize their own energy costs considering the time variable price signals and the model is based on transactions between REPs and consumers [17]. Decentralized HEMS models can lead to additional peak loads [17], and without a coordinating control system which can link the individual HEMSs together they cannot be used effectively for congestion management. Chang et al. [19] developed a decentralized coordinated HEMS in which distributed HEMSs can collaborate with each other. The purpose of the collaboration is to keep demand supply balanced in their neighborhood. REPs send the price signals to the HEMSs. The model is proposed to avoid the rebound effect of the uncoordinated operation of individual HEMSs in a neighborhood on the aggregate demand profile. Although consumption scheduling is done locally in this model, consumers are modeled in a way not behave selfishly. Andersen et al. [20] presented the model of a virtual power plant to implement a centralized control of a large number of houses with HPs. The main focus was put on the virtual power plant setup. However, the model is also usable under different pricing schemes.

In this paper, the DSO implements a market-based mechanism to manage the congestion in distribution network. The concept of economic signaling performed by the DSO involves the REPs in congestion management. The DSO offers DPT and DT to influence the consumption. DTs are elements of LMPs in the distribution network. The LMPs are calculated with optimal power flow models, considering the expected nodal consumptions. Load control is performed by REPs through a centralized coordinated HEMS. They aggregate the flexible demand of their clients. This coordination procedure addresses the limitations of both the DSO and the REPs for executing DR programs. DSOs usually lack the direct interaction and financial relationship with end-users, and REPs lack the access to grid information.

In this paper, consumption scheduling is carried out by the REP based on the requirements of the users without sacrificing the comfort and convenience. The REP plays the role of a demand service provider, and takes into account the preferences of the users. The price signals sent by the DSO also influence the schedules. It is assumed that the payoff maximization is the main objective of the REP. It uses the flexibility provided by the consumers in short-term. Customers are rewarded for the flexibility that they provide. Payment to the consumers is not considered in this model and it does not influence the outcomes of this research as it has focused mainly on a market-based mechanism used by the DSO. It is assumed that the REP pays the consumers later in proportion to the amount of flexibility that they have provided. Several approaches have been proposed in the literature to formulate this interaction [21,22].

In the existing works on demand-side management for alleviating the congestion in distribution networks induced from controllable loads there is no comparison among DTs and DPTs. While the majority of previous works consider only one pricing scheme for congestion alleviation, there is a lack of studies assessing the impact of other pricing schemes rather than the dynamic tariffs. In order to fill this gap in the literature, a centralized coordinated HEMS operated by REPs is developed, which has the potential to reschedule the consumption based on DTs and DPTs. Therefore, the main contributions of this paper are as follows:

- Development of a market-based mechanism for congestion management, which enables the DSO to control the overloading at distribution lines by offering DTs and DPTs.
- Development of a centralized coordinated HEMS model which is managed by the REP and uses the controllable devices of the users, considering the residential buildings as energy hub with thermal storage capability.

The rest of this paper is organized as follows. In Section 2, the concept of centralized coordinated HEMS and the detailed characterization of each controllable load are described. The impact of DTs is not incorporated in this section. In Section 3, the market-based mechanism is proposed. The DSO computes the DTs and distributes it among the REPs. The HEMS model introduced in Section 2 is then extended to incorporate the impact of DTs. Simulations are performed in Section 4 and the performance of the proposed mechanism for congestion alleviation is evaluated. Conclusions are given in Section 5.

2. Coordinated HEMS model

Electricity loads can be classified as flexible and inflexible loads. Inflexible loads or critical loads should be served by the REP [23] without the possibility to change their consumption pattern, whereas the flexible loads have the ability to reduce, increase or defer their consumption in response to the economic signals that the REP sends [24].

The main assumption in this model is that the aggregation of the flexible loads and the scheduling of their consumption is carried out by the REP through a centralized coordinated HEMS. This duty can also be met by an intermediary entity between customers and the REPs, such as DR aggregators. However, changing this assumption does not influence the main purpose of this model, which is alleviating the congestion through DR implementation in distribution networks.

It is worth noting that the active customers should be properly compensated for providing this flexibility for REPs. In this model, scheduling the consumption provides financial benefits for the REPs and the customers' benefit of DR is delivered to them via the discounts in their monthly electricity bills. The customers with whom the REP has contracted for providing flexibility should be remunerated by the relevant REP through a number of mechanisms which may include discounts on the retail rates or on the total electricity bills. The payment method is agreed in the bilateral contract between the customer and REP. Determining the optimal payment method, as well as determining the optimal retail rates are medium-term scheduling problems of the REPs and they are not in the scope of this paper.

The electrification of the transportation system and space heating is a consequence of the policies to eliminate fossil fuels [25]. Although the energy efficient technologies such as EVs for the transportation system and HPs for the space heating reduce the total energy demand, they will increase the electricity demand [26]. Some studies anticipate that full penetration of EVs and HPs will result in a 50% increase in total electricity consumption and a 100% increase in peak demand [25,27]. High penetration of such loads can potentially create overloading in electricity lines [6], as well as increasing the generation requirements [10]. These challenges are even amplified when the consumption of these flexible loads react to price signals, which will lead to a loss of diversity in the on/off cycles and consequently increase the overloading of the electricity lines [6]. The impact of this situation can be compared with the so-called "cold load pick-up" effect after a blackout, which will lead to a spike in demand due to loss of load diversity [6]. When the time variable retail rates are high for several hours, the consumers may postpone the flexible demand and when it reduces the demand may exceed the prior demand [6].

On the other hand, high penetration of these loads in power systems increase the DR potential [25]. Although they present a challenge to distribution networks [28], they can offer means to stabilize the distribution network by providing DR potential [29]. Therefore, a suitably conceived market-based mechanism can get advantage from the flexibility provided by HPs and EVs to alleviate congestions in the distribution system.

The energy requirements of loads can be procured through day-ahead markets. REPs are commercial entities in electricity markets which integrate the demand side resources and submit the bids to the day-ahead market on behalf of the end-use private consumers [5,7,10]. It is not practical for the numerous dispersed small scale resources to directly participate in the wholesale market [5]. The REPs can gain profit by optimally scheduling the consumption of the flexible loads [5]. At the same time, they can also contribute in enabling secure and economic operation of the distribution network [5].

The objective function (1) of the REP computes the total payoff of the company over the scheduling horizon (Payoff_i) and is determined by subtracting the cost of energy purchase at the wholesale market from the sales to end-users. It is assumed that the REP in this model is price taker.

$$\text{Maximize} \quad \text{Payoff} = \sum_{t\in \mathrm{T}} \sum_{c\in C} \left(\gamma_c(t) - \lambda^P(t)\right) \cdot p_c(t) \cdot \tau \tag{1}$$

It is assumed that each consumer in this model is a house. Therefore, the index c is used to represent both consumers and houses. The predicted day-ahead market price is shown with λ^P and the retail rate for each consumer is shown with γ_c. Retail rates can be time variable same as the wholesale market prices and they also may change among the household consumers served by REP (C), depending on the type of the contract that has been made with the REP. Even in a same node the REP might offer different tariffs to consumers. The consumption schedule profile of consumer c (p_c) is composed of the firm load (P_c^{Firm}) and the flexible demand ($p_c^{Flexible}$):

$$p_c(t) = P_c^{Firm}(t) + p_c^{Flexible}(t), \qquad \forall t \in T, \forall c \in C. \tag{2}$$

The flexible demand is a variable and the components of this profile are shown as:

$$p_c^{Flexible}(t) = p_c^{HP}(t) + \sum_{\forall v \in \Omega_{EV}^c} \left(p_v^{Ch}(t) - p_v^{DCh}(t)\right); \quad \forall t \in T, \forall c \in C, \tag{3}$$

where p_c^{HP} is the consumption of the HP located in house c, and p_v^{Ch}/p_v^{DCh} is the charging/discharging power of the EV v.

2.1. Constraints of EV scheduling

REPs schedule the charging and discharging of the EVs that are registered for load control based on the permanent characteristics of the EVs and the preferences of the owners for arrival and departure time. Despite the uncontrolled charging of EVs which charges the battery after being connected to the grid [30], the main control variables in controlled charging scheme are the charging and discharging power during each time period. It is essential to keep them always within the admissible rates. This limitation is formulated as follows:

$$0 \le p_v^{Ch}(t) \le P_v^{Ch,Max} \cdot x_v^{Ch}(t); \qquad \forall v \in \Omega_{EV}, \forall t \in \mathrm{T}_v, \tag{4}$$

$$0 \le p_v^{Dch}(t) \le P_v^{Dch,Max} \cdot x_v^{Dch}(t); \qquad \forall v \in \Omega_{EV}, \forall t \in \mathrm{T}_v, \tag{5}$$

where $p_v^{Ch,Max}$ and $p_v^{DCh,Max}$ are respectively the maximum charging and discharging rates. These rates are restricted by the maximum acceptable charging power of EV battery, maximum power set by the EV user and maximum power EV charger can output. Usually, both the maximum power EV charger can output and the maximum power set by the EV user are greater than the maximum acceptable charging power of the EV battery [31]. The discharged power of the EVs can be used to serve part of the household loads (i.e., vehicle-to-home) or to be injected back to the grid (i.e., vehicle-to-grid) [18,32]. Simultaneous charging and discharging of EVs is avoided with the following constraint on the binary variables x_v^{Ch} and x_v^{Dch}:

$$x_v^{Ch}(t) + x_v^{Dch}(t) \le 1, \qquad \forall v \in \Omega_{EV}, \forall t \in \mathrm{T}_v. \tag{6}$$

The EV's State of charge (SoC) update function is represented as follows:

$$SoC_v(t) = SoC_v^{Initial} + \tau \cdot \left[\eta_{Ch} \cdot p_v^{Ch}(t) - p_v^{Dch}(t)\right];$$

$$\forall v \in \Omega_{EV}, t = \alpha_v. \tag{7}$$

$$SoC_v(t) = SoC_v(t-1) + \tau \cdot \left[\eta_{Ch} \cdot p_v^{Ch}(t) - p_v^{Dch}(t)\right]; \quad \forall v \in \Omega_{EV}, \forall t \in \mathrm{T}^v, t \neq \alpha_v, \tag{8}$$

where Eq. (7) calculates the SoC of the EV at the end of the first time period after the arrival and Eq. (8) calculates the SoC of the EV v at the end of the remaining time periods. The SoC of the EVs' battery should always be within a certain range, which is imposed through the following inequality constraint:

$$SoC_v^{Min} \leq SoC_v(t) \leq SoC_v^{Max}, \qquad \forall v \in \Omega_{EV}, \forall t \in \mathrm{T}_v. \tag{9}$$

Constraint (9) guarantees high battery efficiency during its' lifetime [33]. Although an EV is very similar to a storage system, in terms of operational scheduling, a few extra constraints should be enforced for the charging/discharging status of EVs [33]. For instance, they are only available between the arrival and departure time of the EV (T^v) or the SoC of the EV should be at a specific amount by the departure time. These two characteristics are mathematically described as:

$$x_v^{Ch}(t) + x_v^{Dch}(t) = 0; \qquad \forall v \in \Omega_{EV}, \forall t \notin \mathrm{T}_v, \tag{10}$$

$$SoC_v(t) = SoC_v^d; \qquad \forall v \in \Omega_{EV}, t = \beta_v, \tag{11}$$

where SoC_v^d is the required energy level of the battery at the departure time. Constraint (10) shows that during the periods that the EV is not connected to the grid, charging and discharging tasks cannot be performed. Constraint (11) enforces that the EV should be charged to a specific amount when the user is taking the car for daily trips.

2.2. Constraints of HP scheduling

The house temperature change among two consecutive time periods is proportional to the difference between the heat flow provided by the HP (Q_c^{HP}) and the heat losses (Q_c^{Loss}). The evolution in time of the indoor temperature due to the heat flow/loss is shown by [34,35]:

$$\theta_c^{in}(t) - \theta_c^{in}(t-1) = \frac{\tau}{\mu_c \cdot \chi^{air}} \cdot \left(Q_c^{HP}(t) - Q_c^{Loss}(t)\right); \quad \forall c \in C, \forall t \in T, \tag{12}$$

where the indoor temperature of the house c is shown with θ_c^{in}. The total indoor air mass of the house (μ_c) depends on the characteristics of the house, while χ^{air} denotes the air heat capacity at standard conditions. Constraint (13) represents the range of indoor temperature allowed by the customer. θ_c^{Low} and θ_c^{UP} are the lower and upper bound of the indoor temperature which are set by the end-user and can be time variable, depending on the preferences of the user.

$$\theta_c^{Low}(t) \leq \theta_c^{in}(t) \leq \theta_c^{Up}(t) \tag{13}$$

The heat losses at each period are proportional to the difference between indoor and outdoor temperature:

$$Q_c^{Loss}(t) = \kappa_c \cdot \left(\theta_c^{in}(t-1) - \theta^{out}(t-1)\right); \qquad \forall c \in C, \forall t \in T, \tag{14}$$

where κ_c is the heat loss factor of the house and θ^{out} is the outdoor temperature [34]. The heat flow of the HP at each period is instead given by:

$$Q_c^{HP}(t) = \chi^{air} \cdot f_c^{HP}(t) \cdot \left(\theta_c^{HP} - \theta_c^{in}(t-1)\right); \qquad \forall c \in C, \forall t \in T, \tag{15}$$

where f_c^{HP} is the air mass flow of the HP delivered to the house at the constant output temperature θ_c^{HP} of the HP. In (15), Instead of using θ_c^{in}, the reference temperature θ_c^{ref} of the house (defined as the average between lower and upper boundary temperature) can be used to maintain the linearity of the problem. Since the indoor temperature should always remain in the comfort zone, this approximation is acceptable.

The air mass flow of the HP can be divided into different operating modes, based on the required power of the heat pump to generate that flow. f_c^{HP} is considered as the summation of air mass flows in different modes:

$$f_c^{HP}(t) = \sum_{m \in M_{HP}^c} f_{c,m}^{HP}(t); \qquad \forall c \in C, \forall t \in T, \tag{16}$$

where $f_{c,m}^{HP}$ is the incremental air mass flow associated to each operating mode. In each mode, the air mass flow should be within the defined range:

$$0 \leq f_{c,m}^{HP}(t) \leq x_c^{HP}(t) \cdot \Phi_{c,m}^{HP}; \qquad \forall c \in C, \forall t \in T, \forall m \in M_{HP}^c, m \neq 1, \tag{17}$$

where x_c^{HP} is a binary decision variable which is 1 when the HP is turned on and $\Phi_{c,m}^{HP}$ is the maximum air mass flow at each mode. The air mass flow in the first mode denotes the minimal air mass flow of the HP when it is turned on. Therefore, $f_{c,m}^{HP}$ for the first mode is computed as the following equality constraint:

$$f_{c,m}^{HP}(t) = x_c^{HP}(t) \cdot \Phi_{c,m}^{HP}; \qquad \forall c \in C, \forall t \in T, m = 1, \tag{18}$$

The required power of the HP (p_c^{HP}) is the summation of the required power in each operation mode of the HP:

$$p_c^{HP}(t) = \sum_{m \in M_{HP}^c} f_{c,m}^{HP}(t) \cdot \rho_{c,m}^{HP}; \qquad \forall c \in C, \forall t \in T \tag{19}$$

where $\rho_{c,m}^{HP}$ is the power per air mass flow of each operating mode. $\rho_{c,m}^{HP}$ is monotonic increasing with the delivered air flow ($\rho_{c,1}^{HP} \leq \rho_{c,2}^{HP} \leq \cdots$).

Fig. 1 shows a schematic layout of the HEMS model. The inputs that require a daily update are shown on the left, the built-in or permanent characteristics of EV loads, HP loads and the houses are represented in the middle and the outputs are in the right.

3. Market-based mechanism for congestion management

The regulatory enactments in liberalized markets form a hard boundary that avoids the DSOs to enter direct load control demand response programs to provide grid support services [36]. However, the centralized control of the loads is an important requirement to provide these services. The proposed market-based approach shifts the responsibility of load control from the DSO to REPs. Without a centralized load control, each user will need an energy management system to manage the controllable loads. Moreover, the DSO has to send the price signals to all users, and more investments are required to form this communication system. In the end, it will not even guarantee that the outcome of the users' individual energy management systems can alleviate the congestion or reduce the peak without creating new peaks in the system.

Implementing market-based mechanisms by DSOs requires the participation of other market entities located between consumers and the DSO. REPs in this scheme are usually selected to manage the flexibility from the residential end-users [37]. They play the role of a demand response provider. Consumers are also more willing to react to economic signals sent by the demand response provider rather than being ordered to alter their consumption by the system operator [1].

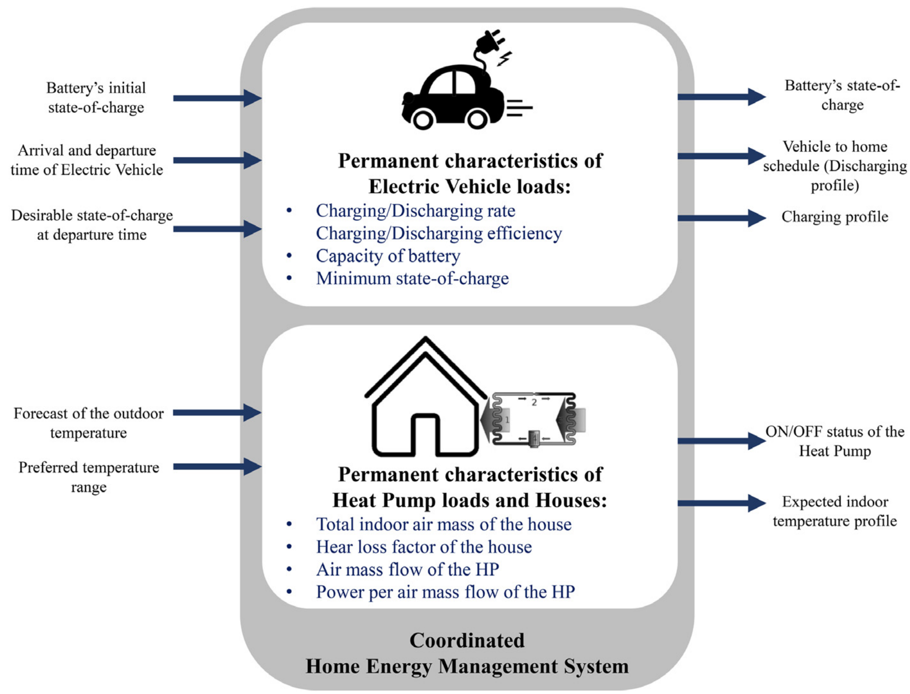

Fig. 1. Schematic of the coordinated HEMS.

3.1. Dynamic tariffs

In this model, the DSO alleviates the congestion in a distribution network through a decentralized approach [8]. The DSO calculates the DTs which reflect the distribution congestion prices and provides the REPs that are serving customers in the distribution network with this information [8]. The REPs individually perform their own energy planning. They optimally schedule the flexible consumption of their clients through the coordinated HEMS, considering the distribution congestion prices. Their bids in the day-ahead market will be obtained based on this schedule. The congestion prices are finally passed to the end-users [6]. The proposed market-based mechanism for congestion management should be completed before market clearing of the day-ahead markets [1]. The DSO uses the historical data to forecast the spot prices as well as the flexible and firm demand [1]. It computes the DTs considering these predicted values and the generation offers of the DGs producing electricity inside the distribution network.

DTs that the DSO offers to REPs for congestion management should reflect distribution congestion prices. Distribution congestion price can be considered as an element of LMPs [1]. Using LMPs in transmission systems is very common. They reflect the marginal cost at each node of the grid, which also incorporates the extra cost due to congestion and energy losses [1]. In this model, the DSO uses DC optimal power flow (DCOPF) to formulate distribution LMPs and obtain the nodal prices of active power [1,5]. With this information, the DSO can attain the DTs. DCOPF is an efficient technique to determine the active power flow in electricity lines [5, 10]. The power flow results obtained from DCOPF are close to those obtained with ACOPF with much less computation time [5]. Therefore, it can be considered sufficient in many cases and several well-known software tools have employed this technique for chronological LMP simulation and forecasting [5]. Fig. 2 shows the relationship between the DSO and the REPs. The DSO runs the OPF and calculates the DTs based on predictions from the market and the retail customers.

The proposed mechanism is a step-wise tariff scheme [10]. In this scheme, system balance and distribution network congestion are tackled independently. Congestion prices are determined by the DSO. The DSO has to predict the total demand and also the day-ahead market prices in order to determine the congestion prices. This approach can be implemented directly in many European electricity markets, unlike the integrated tariffs approach where both system balance and grid congestion needs to be settled in a single step [10].

As the marginal cost of losses does not influence the value of DTs [10], a linearized lossless DC model of the network is considered [38]. It is assumed that the loads can be fully served through the wholesale market and, in the case of congestions, the dispatchable DG units in the distribution network can be used. The costs arise due to the congestion will be later compensated by the consumers [10]. The objective function of the DSO for each time period is to minimize the electricity supply cost in the distribution network [1]:

$$\text{Minimize} \quad \text{Cost} = \sum_{b \in \mathrm{B}} C_b(t) \cdot p_b^g(t); \qquad \forall t \in T, \tag{20}$$

where C_b is the cost of procuring electricity at each bus for the next trading day. It is equal to day-ahead wholesale market price at the bus connected to the transmission network and for other buses, where a DG unit is connected, it is equal to the price that they offer. The DCOPF problem meets the load in power system, while minimizing the total operation cost in the network. It is subject to the following energy balance and transmission constraints [38,39]:

$$\sum_{b \in \mathrm{B}} p_b^g(t) = \sum_{b \in \mathrm{B}} P_b^{Forecasted}(t); \qquad \forall t \in T, \tag{21}$$

$$\sum_{b \in B} GSF_{k-b} \cdot \left(p_b^g(t) - P_b^{Forecasted}(t)\right) \le Limit_k; \qquad \forall t \in T, \forall k \in K \tag{22}$$

$$G_b^{\mathrm{Min}} \le p_b^g(t) \le G_b^{\mathrm{Max}}; \qquad \forall b \in B, \forall t \in T \tag{23}$$

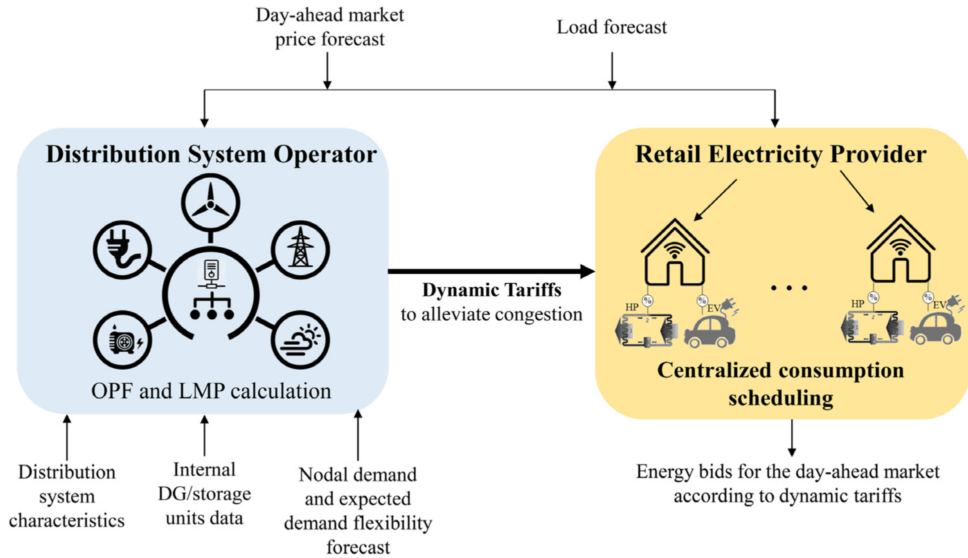

Fig. 2. Schematic of the proposed market mechanism.

In (21), $P_b^{Forecasted}$ is considered as an input. DSO can use predicted values for this parameter or the results of the REPs' initial load scheduling.

The line flow limitation is represented with GSF in the DCOPF problem. GSF_{k-b} is the generation shift factor to line k from bus b, which depends on the selection of the reference bus [40]. GSF is the ratio of the change in power flow at line k to the variation in power injection at bus b [41]. The reference bus in this set of formulations is the bus connected to the transmission grid. However, it is worth noting that the electricity flow limits in (22) are independent from the reference bus choice [40]. $Limit_k$ is the line power flow limit at line k.

LMP is composed of three elements: energy price, congestion price and loss price [41]. In the DC lossless power flow, the loss price is zero and therefore the LMP at each bus is composed of the marginal price of generation at the reference bus and the marginal congestion price at that node [42].

$$\lambda_b^{LMP}(t) = \lambda^{Energy}(t) + \lambda_b^{Congestion}(t) + \lambda_b^{Loss}(t); \qquad \forall b \in B, \forall t \in T. \tag{24}$$

LMP at each bus of the distribution system can be attained by solving the above DCOPF model. LMP at each bus is mathematically defined as the dual variable of the power balance constraint at that node [41]. The Lagrangian function of the DCOPF problem is calculated as follows:

$$\begin{aligned}\Psi(t) = &\left(\sum_{b\in B} C_b(t)\cdot p_b^g(t)\right) - \omega(t)\\ &\cdot\left(\sum_{b\in B} p_b^g(t) - \sum_{b\in B} P_b^{Forecasted}(t)\right)\\ &-\sum_{k\in K}\mu_k(t)\cdot\left(\sum_{b\in B} GSF_{k-b}\cdot\left(p_b^g(t) - P_b^{Forecasted}(t)\right)\right.\\ &\left.-Limit_k\right); \qquad \forall t \in T\end{aligned} \tag{25}$$

where ω and μ_k are respectively the Lagrangian multipliers of constraints (21) and (22) [10]. The LMP is calculated as [10]:

$$\lambda_b^{LMP}(t) = \frac{\partial\Psi(t)}{\partial P_b^{Forecasted}(t)} = \omega(t) + \sum_{k\in K}\mu_k(t)\cdot GSF_{k-b}; \qquad \forall b \in B, \forall t \in T. \tag{26}$$

$\omega(t)$ is the locational marginal energy price and $\sum_{k\in K}\mu_k(t)\cdot GSF_{k-b}$ is the locational marginal congestion cost [10], which is used by the DSO as the congestion prices. Thus, the congestion price at each bus and each time period is calculated as:

$$\lambda_b^{Congestion}(t) = \sum_{k\in K}\mu_k(t)\cdot GSF_{k-b}; \qquad \forall b \in B, \forall t \in T. \tag{27}$$

Charges appear when the electricity lines are constrained by physical limits [41]. The congestion cost is associated with the line flow constraints [42]. The DSO publishes these congestion costs as DTs for the REPs to consider in the consumption scheduling procedure to alleviate the possibility of congestion occurrences.

The REP incorporates the impact of DTs in its objective function (1) and the consumption of household appliances is optimally scheduled in response to price signals. The price signals are composed of the DTs published by the DSO and the predicted day-ahead market prices [10]. It is worth noting that despite the day-ahead market price, which does not vary among nodes, the DT is defined on the single nodes to alleviate the expected congestion. The new objective function of the REP is as follows:

$$\begin{aligned}\text{Maximize}\quad \text{Payoff}_i = &\sum_{t\in T}\sum_{b\in B}\sum_{C\in C_b}\left(\gamma_c(t) - \lambda^P(t) - \lambda_b^{Congestion}(t)\right)\\ &\cdot p_c(t)\cdot\tau.\end{aligned} \tag{28}$$

This DR scheme can be used as an alternative to RTP tariffs and time-of-use (TOU) pricing schemes. This centralized coordinated HEMS allows REPs to control flexible loads that are being served under fixed retail tariffs.

The DTs increase the energy price for consumers during specific hours, which can impact the consumption pattern of the users. The end-users may prefer to shift their loads more to the periods with lower prices, which may cause a rebound effect and create new peak demands at periods not expected. Therefore, the DSO should use price schemes that charge the end-users according to their peak demand. Tariffs such as DPTs avoid peak demand spikes at other periods.

3.2. Daily power-based network tariffs

Another pricing system to avoid congestion occurrences in distribution networks is to use DPTs [44], where the consumers are

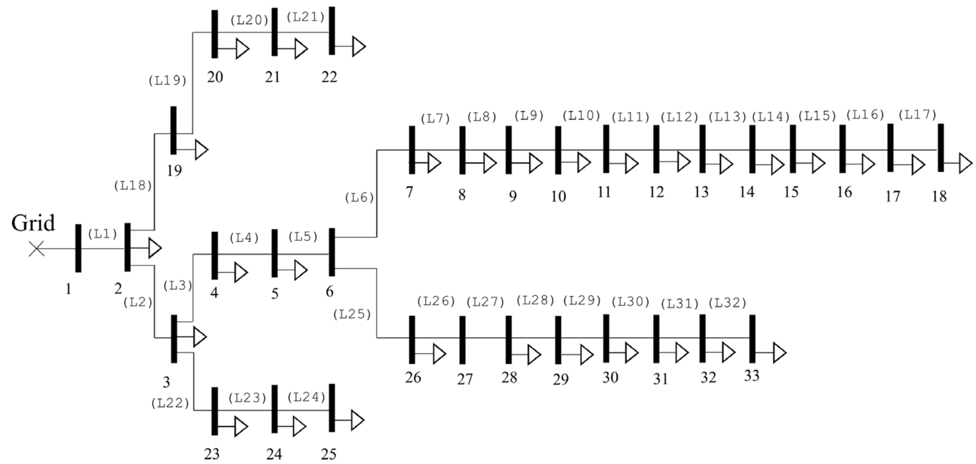

Fig. 3. IEEE 33-bus distribution system [43].

charged for the maximal power consumption [45]. This network pricing scheme gives REPs an incentive to reduce the maximal power consumption at each node [45]. Employing this pricing system for consumers with an uncoordinated distributed HEMS is not as efficient as using this scheme with a coordinated centralized HEMS, because the maximal power use of customers may not coincide with the aggregated peak-demand in the nodes of the distribution network. This price system is being considered by DSOs in many electricity markets [45]. The objective function of the REP is in this case as follows:

$$\text{Maximize} \quad \text{Payoff}_i = \sum_{t\in \mathrm{T}}\sum_{b\in B}\sum_{C\in C_b}\left(\gamma_c(t) - \lambda^P(t)\right)\cdot p_c(t)\cdot\tau - \sum_{b\in B} p_b^{Peak}\cdot\lambda_b^{DPT} \tag{29}$$

where p_b^{Peak} is the daily peak demand and λ_b^{DPT} is the DPT at bus b. As the DSO runs the DCOPF with hourly time intervals, the p_b^{Peak} is defined as:

$$\sum_{t\in T_h} p_b(t)\cdot\tau \le p_b^{Peak}; \qquad \forall h, \forall b. \tag{30}$$

The DSO can apply both DTs and DPTs simultaneously. In this case, the objective function of the REP is represented as:

$$\text{Maximize} \quad \text{Payoff}_i = \sum_{t\in \mathrm{T}}\sum_{b\in B}\sum_{C\in C_b}\left(\gamma_c(t) - \lambda^P(t) - \lambda_b^{Congestion}(t)\right)\cdot p_c(t)\cdot\tau - \sum_{b\in B} p_b^{Peak}\cdot\lambda_b^{DPT}. \tag{31}$$

4. Case study and discussion

The modified IEEE 33-bus distribution is used in this section to validate the effectiveness of the proposed method. The topology of the 12.66 kV system is shown in Fig. 3. This test system contains 30 load buses. In this case study, it is assumed that one REP is serving all the residential customers. The distribution of the residential customers among the buses of the distribution network is shown in Fig. 4. In this test system 706 residential consumers are being served by the REP. The scheduling horizon, which is 24 h, can begin at any time of the day. In this paper, the starting time of the scheduling is not necessarily at the beginning of the day. Time intervals for the REP's consumption scheduling is 15 min, and it is 1 h for the DSO. Therefore, there are 96 time periods in the consumption scheduling. The aggregated inflexible demand profile of the consumers and the hourly day-ahead market prices are shown in Fig. 5. The inflexible demand is extracted considering a standard aggregated pattern for residential customers related to a typical working day in January, which is derived from a German database [46]. The day-ahead market prices are taken from the Iberian Electricity Market (Mibel) [47]. It is assumed that all customers are being served at the fixed retail rate of 0.17 €/kWh.

Table 1
House models.

House models	Heat loss factor of the house [W/°C]	Total indoor air mass of the house [kg]
1	191,200	367.50
2	250,300	551.25
3	312,400	1960.00

All residential customers in this test system have EV and HP loads. Several house models and EV types are listed in Tables 1 and 2. It is assumed that the residential consumers live in one of the house models listed in Table 1 and own one of EV models shown in Table 2. The house type and the EV model of each customers is selected randomly. The heat loss factor of the house and the total indoor air mass of the house depends on the geometric dimensions of the house, including the characteristics of the walls and windows [34].

It is assumed that the expected battery energy level of the EVs at the departure time can be achieved at the interval that the EV is connected to the grid. The average connection time of the EVs into the grid is 45.61% of the scheduling horizon. The EV availability during the scheduling horizon is shown in Fig. 6. The number of time periods that different numbers of EVs are connected to the grid is shown in this figure. It shows that during 19 time periods out of the total 96 time slots, 70%–80% of the total number of EVs are connected to the grid, and hence available for controlled charging. The maximum availability occurs at time period 60 when 81.02% of the EVs (e.g., 572 EVs) is connected to the grid. The mean arrival time of EVs is at time period 31 ± 17 and mean departure time is at 74 ± 17. Charging and discharging power can be scheduled from zero to a maximum which is the charging/discharging rate of the EV. It is assumed that the EV is charged constantly during each 15-minutes time interval.

The operation modes of the HPs are shown in Table 3. It is assumed that all HPs are from the same models, but can function at different operating points. The lower and upper indoor temperature bound determined by the users are shown in Fig. 7. In this figure, the hourly outdoor temperature for the 24 h scheduling horizon is also shown.

The following four cases of consumption scheduling are studied in this paper to provide a comparison between DTs and DPTs in alleviating the congestion.

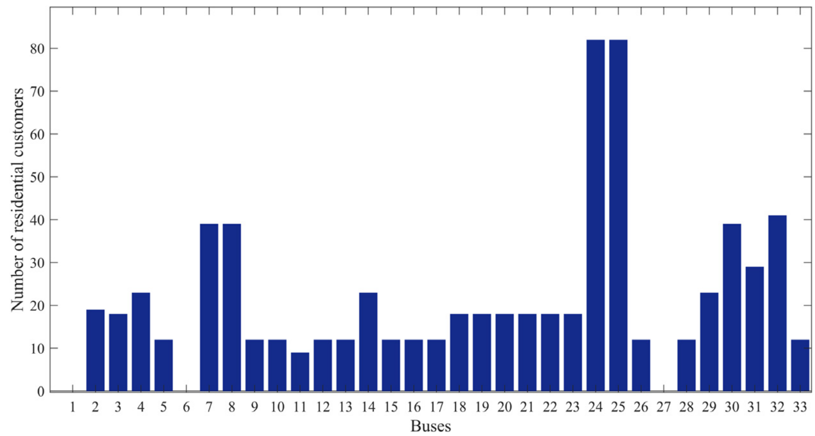

Fig. 4. Number of residential consumers at the buses.

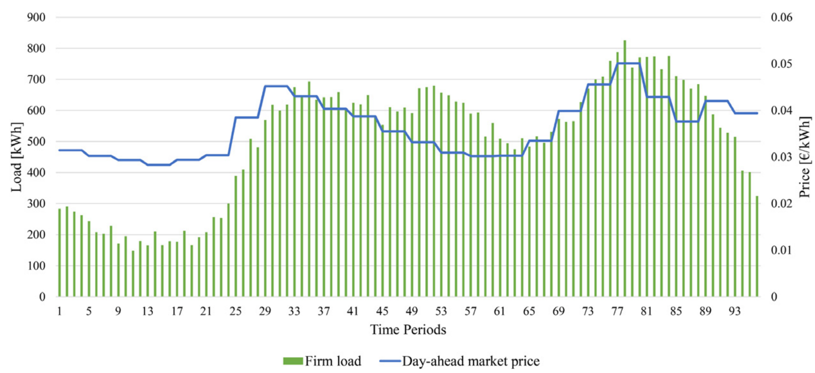

Fig. 5. Forecasted firm loads of all customers and the day-ahead market price.

Table 2
EV models [18].

EV models	Battery capacity [kWh]	Minimum battery energy level [kWh]	Charging rate [kW]	Discharging rate [kW]	Charging efficiency	Discharging efficiency
1	16.0	2.0	3.30	3.30	0.90	0.91
2	24.0	2.9	2.00	1.70	0.91	0.85
3	60.0	9.2	6.60	5.10	0.88	0.87
4	19.0	1.9	3.00	2.40	0.86	0.90
5	23.0	3.2	3.30	3.00	0.83	0.86
6	10.3	1.4	2.00	1.70	0.89	0.91
7	30.0	3.3	3.30	2.70	0.85	0.87
8	28.0	3.5	2.60	2.50	0.82	0.90

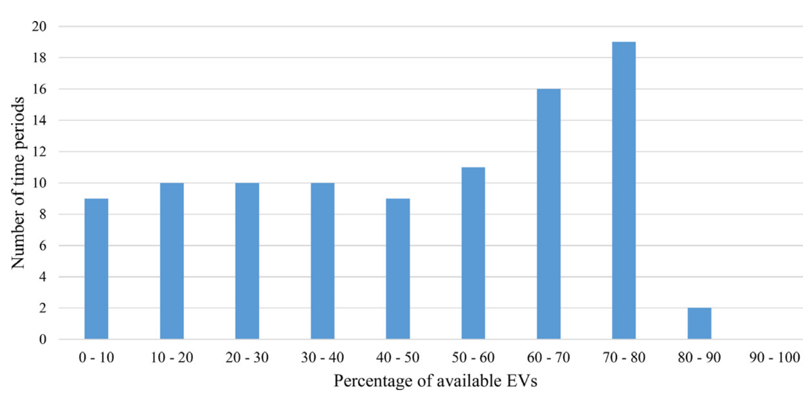

Fig. 6. EV fleet availability.

- Case 1: no pricing signals for congestion management;
- Case 2: DTs as the pricing signals;
- Case 3: DPTs as the pricing signals;
- Case 4: both DTs and DPTs as the pricing signals.

For cases 2 and 4, in which DT is incorporated in the decision-making model of the REP, it is essential to firstly run the DSO's optimization problem with the forecasted nodal demand as input. In this problem, it is essential to include the line loading limits. In

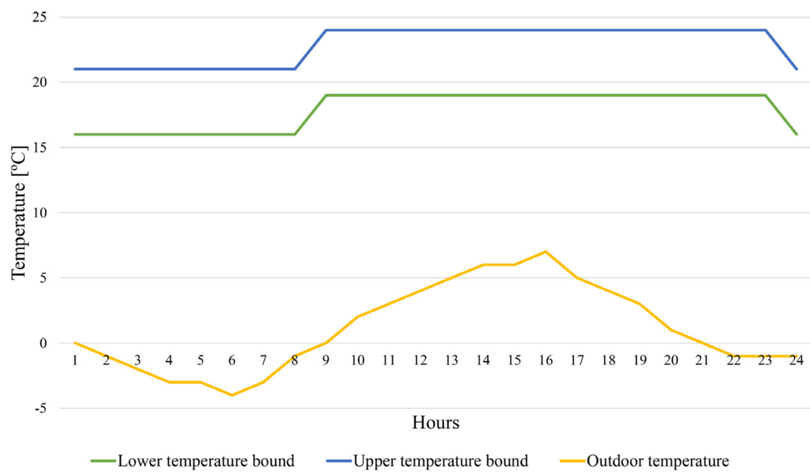

Fig. 7. Forecasted outdoor temperature and the indoor expected temperature range.

Table 3
HP operation modes.

HP modes	Maximum air mass flow [kg/h]	Power per air mass flow [Wh/kg]
1	426	0.94
2	264	1.86
3	178	3.70

Table 4
DPTs published by the DSO.

Hours	DPT (€/kWh)
2-5, 23–25	0.0056
7–18	0.0084
19–22	0.0091
26–33	0.0078

the case of overloading, the internal dispatchable DG units can be used to serve the consumers. They produce electricity at higher prices compared to the wholesale market. After determining the DTs and publishing them, the REP schedules the consumption based on these tariffs. In order to compute the overloading at distribution lines, the DSO problem is solved without considering the line loading limits. The DTs and DPTs are respectively shown in Fig. 8 and Table 4. DTs are the congestion prices introduced in Eq. (27). DT is a component of LMP at the distribution grid. It is determined by the DSO using the set of Eqs. (20)–(27). The DPTs are considered as inputs in this model. The DSO offers them in 4 different price steps to the REPs. The DSO's historical data about the grid congestions and the energy demand in the grid are the main determinants for setting these tariffs.

The results of the case studies are shown in Table 5. All cases in this section, which include the problem of REP and the DSO, are solved by CPLEX [48] with GAMS 24.4.6 [49] on a 2.1 GHz Intel Xeon processor executed on 16 GB RAM and 64-bit Windows 8.1 Pro system. The computational peak memory for the REP's problem in case 4, which includes both price signals, is 164 MB and the execution time for this problem is 340 s. The computational peak memory for the DSO's problem is 52 MB with the execution time of 130 s.

Although applying DTs have reduced the number of overloading occurrences and the average of the overloading magnitude, the DSO can still expect severe congestions at the periods in which these tariffs are not considered. On the other hand, the case study results reveal that considering DPTs (i.e., case 3) is very effective in alleviating the congestion, without having considerable impact on the REPs' payoff compared to case 2, in which the DTs are used to manage the congestion. In case 3, the REP uses more the energy stored in the EVs' batteries to serve the demand in order to reduce the peak demand. It uses the V2H 7.11% more compared to case 2. In case 4, which uses both DT and DPT pricing systems to manage the congestion, no overloading occurs.

In order to better analyze the performance of the proposed market-based approach, overloading at line L19 is demonstrated in Fig. 9. Line L19 loading is due to the loads at buses 20, 21 and 22. The aggregated load profile of the firm demand for the 54 residential customers located at buses 20, 21 and 22 is shown in Fig. 10. As shown in Fig. 9, the line loading has decreased significantly during the periods that the DTs are applied. In case 1 overloading at line L19 occurs during hours 13–17, in case 2 it occurs at hours 11, 12, 18 and 22, and in case 3 the overloading happens during hours 12–17. The congestion at line L19 has been fully alleviated in case 4. When the DTs are considered without DPTs, a significant overloading can occur at other periods. For instance, the overloading at L19 has increased to 153.02% at hour 12, which is even higher than the maximum overloading in the case that no tariffs are considered for congestion management (i.e., case 1). The DTs are defined for hours 13–17, and the line loading in case 2 during this interval reduces to 23.72% of the maximum line loading limit, which is far below the 130.37% of the maximum line loading in case 1.

In Fig. 11, the level of energy stored in the EVs batteries connected to bus 20 is shown for the 4 cases. As expected when the DTs and DPTs are not applied, the EVs are charged during the low price periods. As seen in Fig. 9, the maximum overloading occurs at hour 15 (i.e., time periods 57–60). The batteries' energy level shows a significant increase in the energy level of the EV fleet during this interval. In cases 2 and 4, during the periods before hour 13 (i.e., time period 49), the energy level of the batteries is increasing significantly, which shows charging of the EVs. From time period 49, which is the first time period with DTs, the energy level remains almost constant and begins to reduce due to the discharging power.

The approach proposed in this paper is a step-wise approach. The main concern in such models is the difficulty in obtaining a socio-economically optimal solution [10]. This approach can be used in electricity markets without imposing alteration to the structure of the current day-ahead markets.

5. Conclusions and future work

A market-based mechanism for congestion management in active distribution networks is proposed in this paper. Uncontrolled operation of flexible loads, such as EVs and HPs can add demand at peak hours and cause congestion in distribution networks. All pricing systems proposed to alleviate congestion at the distribution network requires an effective load scheduling module which

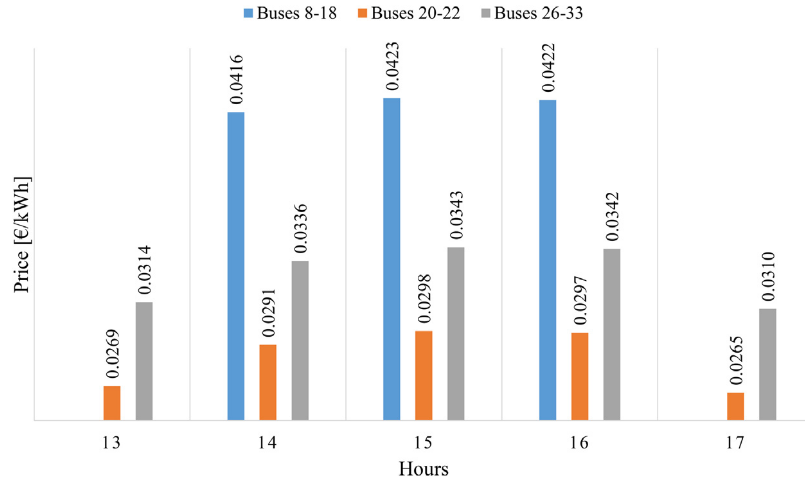

Fig. 8. DTs published by the DSO.

Table 5
Comparison of case study outputs.

	Number of overloading occurrences	Average overloading magnitude (Mean ± SD)	Maximum overloading magnitude	REP's payoff [€]	V2H energy transaction [kWh]	HP energy consumption [kWh]
Case 1	22	123.04% ± 13.39%	145.27%	3505.63	2445.10	201.58
Case 2	16	116.75% ± 13.46%	153.02%	3453.02	2368.80	201.70
Case 3	11	103.25% ± 1.20%	104.31%	3427.17	2537.30	202.80
Case 4	0	–	-	3382.38	2425.50	201.45

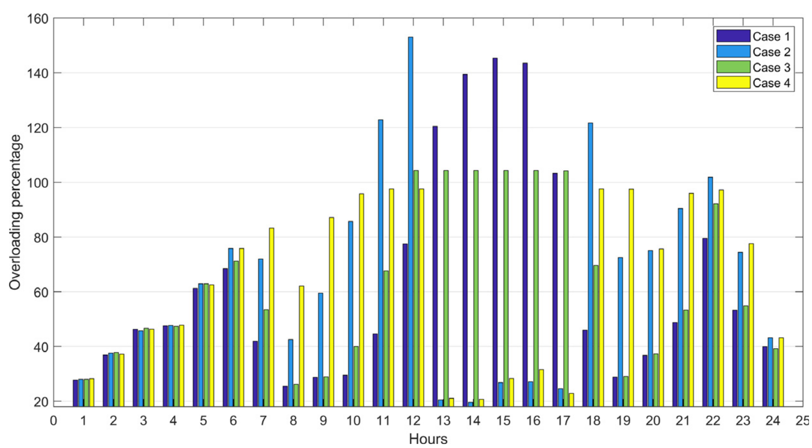

Fig. 9. Loading percentage in line L19.

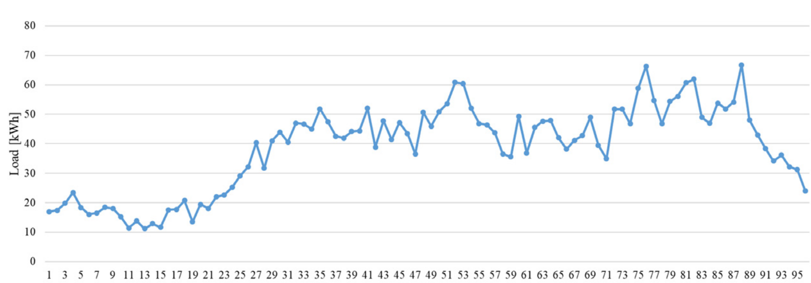

Fig. 10. Aggregated load profile of the firm demand at buses 20, 21 and 22.

provides centralized control for the loads. In this paper, the REP manages the controllable loads of its clients through a centralized coordinated HEMS. The proposed smart consumption scheduling manages the load efficiently and avoids peak demand. It schedules the loads based on day-ahead market prices, DTs and DPTs. DTs and DPTs are the pricing signals published by the DSO to mitigate possible congestions. The optimization problems of the DSO and the REPs are both formulated and solved as MILP problems. The case study results revealed that the DTs cannot individually avoid the congestion occurrences, although they reduce the frequency

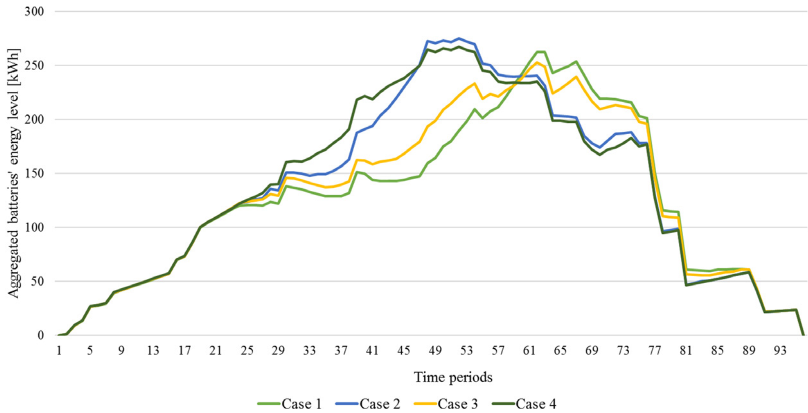

Fig. 11. Aggregated batteries' energy level at bus 20.

of this phenomenon. The simultaneous application of both DTs and DPTs was effective in mitigating the risk of line overloading occurrences.

In the proposed market-based mechanism the DSO and the REP have to make optimal decisions based on forecasted values. It is very difficult to precisely forecast these inputs of the model, and this process always involves a significant level of uncertainty. In the proposed congestion management problem, the problem has been considered as a deterministic model. Our future work will examine the impact of price and demand forecast uncertainty on the alleviation of congestion in the distribution network.

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