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On the application of Home Energy Management Systems for power grid support

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ABSTRACT

Home Energy Management Systems (HEMSs) are being implemented for residential energy management in various parts of the world. Conventionally, a HEMS is developed from the consumer's perspective, with the principal aim of cost-saving while maintaining optimal consumers' comfort. In recent years, various Demand Response programs are being incorporated into HEMSs to address the power grid constraints. In this paper, the functionality of grid support through the HEMSs is presented. The developed scheme utilizes an agent-based coordination mechanism in an active distribution network and manages the household appliances to comply with thermal and voltage constraints of the grid. The proposed mechanism is evaluated through simulation of a typical Dutch low-voltage (LV) residential feeder. A hardware prototype has also been developed and tested in the laboratory environment. The proposed methodologies show promising perspectives for local voltage-violation support and direct load control for congestion management of the grid.

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1. Introduction

Modern residential buildings are now coupled with various electricity generation and storage facilities due to advances in generation and storage technologies, favorable regulations, and demand response (DR) programs [1]. In addition to that, new forms of electrical loads are being integrated into residential buildings including electric vehicles (EVs), heat pumps (HPs), and electric heating, ventilation & air-conditioning (HVAC) systems. Proper management of these building loads and distributed energy resources (DERs) can lead to significant cost savings for the consumers [2–4]. Therefore, Home Energy Management Systems (HEMSs) are being increasingly adopted by residential consumers [5], and advanced variants, incorporating various forecasting and optimization techniques are emerging [5–8]. While traditional HEMSs are designed from the consumer's perspective, evolving electricity market structures allow HEMSs to trade consumers' flexibility in different electricity markets either directly [4] or via service providing aggregators [9,10].

However, fast-growing peak-demand and rapid DER integration

often violate voltage and thermal constraints of the residential networks [11,12]. Therefore, large scale adoption of uncoordinated HEMSs can impose capacity challenges in the low-voltage (LV) residential networks by introducing grid congestions and voltage limit violations, where grid congestion refers excess power flow through grid assets (such as cables, transformer, etc.) beyond their rated capacity. Conventionally, grid capacity issues have been tackled by reinforcing the assets. However, regular grid reinforcement necessitates a huge investment and can be redundant due to the relatively shorter duration of the peak-demands [13]. Distribution System Operators (DSOs) worldwide have therefore been moving towards a more decentralized and intelligent operation involving active consumers' engagement to facilitate greater overall flexibility and reliability in the grid [14].

Significant research efforts have also been made towards developing effective methodologies to utilize the flexibility of DERs and controllable loads for various grid assistance services including congestion management and local voltage control. For example, various pricing strategies have been explored for effective utilization of the consumers' flexibility to alleviate grid congestion, such as distribution locational marginal pricing [15], dynamic subsidy scheme [16], distribution congestion price model [17], etc. A distributed and coordinated EV management system is proposed in Ref. [18] to tackle local capacity issues of higher EV integration.

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Nomenclature			
<i>Indices and sets</i>		$t_k, \bar{t}_k$	Start and end time periods in desired window of operation
$k \in K$	Residential devices	E^{cap}	Rated storage capacity [kWh]
$K_{bd} \subset K$	Buffer devices	m_k, A_k	Thermal mass and thermal insulation of refrigeration appliances
$K_{id} \subset K$	Inelastic devices	p^{cd}, p^{dis}	Charging & discharging power
$K_{ra} \subset K$	Refrigeration appliances	p^{id}	Power demand/generation of inelastic devices
$K_{sd} \subset K$	Shiftable devices	p^{ra}	Nominal power rating of refrigeration appliances
$K_{shc} \subset K$	Space heating-cooling appliances	p^{sd}	Nominal power rating of shiftable devices
$t \in T$	Time periods	Q^{int}	Buildings' internal heat gain
$T^{des} \subset T$	Desired window of operation	r, x	Line resistance and reactance of LV feeder
<i>Parameters</i>		x_{max}	Maximum priority index
α	Heat transfer coefficient	<i>Variables</i>	
β	Thermal discomfort penalty coefficient	ΔP^{uv}	Required power curtailment for under voltage control
Δt	Duration of time periods [hr]	ΔT^{rem}	Remaining time periods in desired window of operation
$\Delta T_{t,k}^{req}$	Time required to complete operation [hr]	λ	Internal control signal
η^{cd}, η^{dis}	Charging & discharging efficiencies	ϕ	Thermal comfort index
η_k	Coefficient-of-performance of refrigeration appliances	σ	State-of-charge of buffer devices
γ	Coefficient-of-performance of space heating-cooling appliances	Θ	Internal temperature of refrigeration appliances
λ_{max}	Maximum value of dynamic price signal	θ	Indoor temperature
$\bar{p}^{shc}$	Maximum power rating of space heating-cooling appliances	C	Operation cost of space heating-cooling appliances
ρ, V, C^B	Air mass density, volume and thermal mass of the building	c	Operating cycles
Θ_t^0	Ambient temperature	D	Thermal discomfort
θ^{out}	Outdoor temperature	d	Bids
θ^{set}	Indoor temperature set-point	f	Flexibility
$\underline{\sigma}_k, \bar{\sigma}_k$	Minimum and maximum state-of-charge	P, Q, S	Real, reactive and apparent power
$\underline{\theta}_k, \bar{\theta}_k$	Minimum and maximum internal temperature of refrigeration appliances	p^{curt}	Power curtailment request of DSO
$\underline{\theta}_k, \bar{\theta}_k$	Minimum and maximum indoor temperature	p^{total}	Total power consumption of a house
		pf	Power factor
		Q^{ex}	Heat exchanged through building surfaces
		Q^{gen}	Generated heat of space heating-cooling appliances
		v	Node voltage
		x	Priority index

Optimization-based [19,20], and game-theoretic [21,22] scheduling models are also investigated for price-responsive consumers of residential communities focusing on peak-demand management. A DR model for congestion management is presented in Ref. [23], where the DSO procures the consumers' flexibility via local aggregators based on the aging cost of distribution transformers. Such local aggregation of consumers' flexibility is also explored in Refs. [4,14,24,25] for local grid support services, whereas the authors in Refs. [9,10] used consumers' flexibility aggregation and proposed optimal market mechanisms for the aggregator to maximize profits. However, the methodologies in Refs. [9,10] do not include any grid assistance functionalities of HEMS and the market-based approaches of [4,15–23] for local grid support services are highly dependent on the availability of demand flexibility and might not be able to tackle the congestions at all times [26]. Direct-load-control (DLC) methodologies are also explored in several studies [25,27] that curtails consumers' load consumption or power injection from DER to address grid congestions and local voltage-constraints violation. However, such approaches raise significant concerns over consumers' privacy and comfort [14,28]. Several studies proposed integrated approaches incorporating market-based methods with suitable DLC that utilize consumer's flexibility when available and limit network access through curtailment request to the point of connection (POC) of the consumer buildings

during grid congestions [14,29] or when the voltage at the POC exceeds allowed limits [24]. Authors in Ref. [14] demonstrated that such integrated methodologies can enhance the flexibility of LV networks and provide a reliable congestion management platform for the DSO.

However, real-world implementation of such active consumer engagement requires a reliable and efficient HEMS that can coordinate these flexibility support processes and act independently in grid services on behalf of the consumer while ensuring cost minimization and comfort reservation for the user. While uncoordinated methodologies in Refs. [23–25] can potentially lead to load synchronization and rebound peaks [30,31], coordinated approaches in Refs. [4,15–21,23,31], despite enhancing overall efficiencies, require complex communication and computations thereby making them difficult to implement in cost-effective and readily available embedded devices for HEMS [8]. Besides, in most of these models do not active consumer bidding for flexibility services [15–17,20–22,31] thereby stripping them off from decision-making authority and some models often exclude consumer's comfort [14,21,25] while defining their flexibility. On top of that, coordinated and consumer-centric approaches of [21,22,31] mainly focuses on cost savings and the peak load reduction in some cases, which can often lead to limited flexibilities for the DSO. In this regard, the inclusion of appropriate power curtailment

schemes at the HEMS can facilitate more flexibility for the DSO in terms of thermal and voltage control management. Moreover, the methodologies in Refs. [15–18,20–22] involve day-ahead schedules of building loads and DERs that consider predictable consumption and appliance usage of the consumers. However, the higher degree of uncertainties in consumers' demand and availability of DERs reduce the reliability of such scheduling models. Such uncertainties are incorporated in Refs. [9,10] by using a two-stage stochastic optimization model [9], and robust optimization algorithm [10]. However, such methodologies require complicated computational capabilities, which make them infeasible for practical implementation with economic embedded devices. Besides, from conveniences perspective, a HEMS should be able to accommodate real-time consumer's preference to address myopic end-users' behavior [4].

This paper presents a cost-effective and easily implementable HEMS model for a market-based real-time local supply-demand coordination with DLC-based thermal and voltage control functionalities for the DSO that aims at cost minimization, comfort maximization, and preferences reservation for the consumer. The interactions between different stakeholders involved in local power balance are realized using multi-agent system (MAS) as it allows them to engage actively in the local supply-demand coordination mechanism while satisfying their own objectives [32–34]. The use of MAS-based architecture also allows active engagement of consumer via HEMS while providing them with full decision-making authority. Flexibilities of building loads and energy resources are incorporated into the HEMS that ensure minimum operational cost while maintaining optimum user comfort and satisfying the preferences of the user. Contrary to most grid-supportive HEMS models, this paper adopts a real-time supply-demand coordination mechanism instead of a day-ahead schedule to manage building loads and DERs. As a result, it enables the HEMS to address the myopic consumers' behavior and uncertainty of demand flexibility by determining flexibility bids according to real-time preferences instead of computation-extensive optimization algorithms [4]. The concept of the aggregator is used in this paper for local flexibility aggregation of the HEMS. The use of aggregator increases the scalability of the proposed methodology [14,24]. Besides, the effect of individual HEMS on the grid is quite negligible compared to aggregated effect [9,35,36], therefore, direct interaction with a huge number of HEMS for grid support services would be redundant and economically infeasible from grid operators' perspective as it would require frequent and complicated communication. An active power curtailment based congestion management and voltage-violation support functionalities are integrated into the HEMS model to address grid capacity issues. The proposed methodology requires simple communications and computational intelligence and implemented in a practical environment with low cost and easily available embedded devices by enabling them with MAS-based distributed intelligence. The key contributions of this paper can be summarized as follows:

- An improved MAS-based HEMS model is presented with the optimal bidding model focusing on cost minimization and comfort maximization for the consumer.
- An active power curtailment based congestion management and local voltage-control method is developed that curtails the energy consumption and/or injection of the house during grid congestions and voltage limit violations.
- A laboratory prototype of the HEMS has been implemented using low-cost and readily available embedded devices with MAS-based local intelligence to evaluate the adaptability of the proposed grid support functionalities of the HEMS in practical situations.

The remainder of the paper is organized as follows. The MAS architecture for the supply-demand coordination is discussed in Section 2, the HEMS model is presented in Section 3, and Section 4 discusses the methodologies of power grid support through the HEMS. The description of the simulation studies are elaborated in Section 5. Finally, the laboratory prototype is highlighted in Section 6, followed by the conclusion of the paper in Section 7.

2. MAS architecture for supply-demand coordination

The agent-based distributed energy management approaches allow active engagement of involved stakeholders, therefore has been widely studied for supply-demand matching of active distribution networks [14,32–34,37]. This paper adopts a MAS-based bidding strategy for supply-demand coordination in residential LV networks as discussed in Refs. [14,23,25]. The coordination is performed in the MAS environment with internal control signals (λ) expressed in per-unit values ranging from 0 to 1. The interaction among the actors in the MAS environment is depicted in Fig. 1. The residential loads and DER units are specified as devices and represented by device agents (DAs) in the MAS environment. Each DA generates demand bids for the associated device, which represent its projected power consumption (or supply in case of DG or DER) as a function of the local control signal, λ . Fig. 2a shows example bids of DA as a function of the control price signal, λ .

As shown in Fig. 1, the HEMS is responsible for gathering all the bids from the devices and sending them to the aggregator. An aggregator coordinates a cluster of buildings in the MAS environment, combines the collected bids and calculates the equilibrium price λ^* for the cluster by matching the local supply and demand as indicated in Fig. 2b. Therefore the value of λ for which the aggregated bid is zero represents the equilibrium price λ^* as it indicates a balanced situation (demand and supply are matched). However, if local demand does not match with local supply, the maximum value of λ is assigned as λ^* and the public grid is used to buy additional demand or to sell additional supply. This equilibrium price signal is then sent back to the device agents via the corresponding HEMS, based on which the DA dictates the operation of associated devices.

Fig. 1. Interaction among the actors in the MAS environment.

Fig. 2. Example bids of DA and supply-demand coordination of aggregator.

3. Agent-based HEMS model

The following sections discuss the mathematical model of the different building devices along with their bidding strategy for the MAS-based supply-demand coordination methodology discussed in Section 2.

3.1. Inelastic device

Inelastic devices include uncontrollable building appliances that need to be operated irrespective of the tariff. The generated power from DG units is also deemed completely uncontrollable, hence considered as inelastic. The bids for such devices are depicted by a constant demand (or supply for DG) irrespective of the values of λ , and represented as:

$$d_{k,t}(\lambda) = P_{t,k}^{id} \quad \forall \lambda \in \{0, 1\}, t \in T, k \in K_{id} \quad (1)$$

3.2. Shiftable devices

Residential appliances whose operation can be shifted in time without affecting the users' comfort are categorized as shiftable devices, such as washing-machines (WM), cloth-dryers (CD) and dishwashers (DW). The DAs of shiftable devices generate bids based on the desired operation window ($T_k^{des} \in [t_k, \bar{t}_k]$) specified by the user and the required operational time (ΔT_k^{req}) according to the operating mode selected by the user, i.e.:

$$d_{k,t}(\lambda) = \begin{cases} P_{c,k}^{sd} & \forall k \in K_{sd}, t \in T_k^{des}, \lambda \geq f_{t,k}, c_k > 0 \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where the operating cycle is represented by $c_k \in [0, \bar{c}_k]$ with $c_k = 0$ indicating the idle state and $\bar{c}_k$ is the maximum required cycles according to the selected operating mode. The flexibilities of shiftable devices are calculated as:

$$f_{k,t} = \frac{\Delta T_{k,t}^{rem} - \Delta T_k^{req}}{\Delta T_k^{req}} \lambda_{max} \quad \forall k \in K_{sd}, t \in T_k^{des} \quad (3)$$

where $T_{k,t}^{rem}$ is the remaining time periods in the desired operating window, i.e.:

$$T_{k,t}^{rem} = \bar{t}_k - t \quad \forall k \in K_{sd}, t \in T_k^{des} \quad (4)$$

3.3. Thermal devices

Temperature-dependent residential devices are considered as thermal devices, and include refrigerator, freezer (FR), air-conditioners (AC), HP and HVAC systems. Thermal devices are divided into the following two groups for the HEMS:

3.3.1. Refrigeration appliances

Domestic refrigerators and freezers used for cold storage are considered as refrigeration appliances. Ideally the internal temperature of a refrigerator is 4 °C and less than −18 °C for a freezer. However, a flexible temperature range is considered for these devices and modeled as [38]:

$$\Theta_{t,k} = \frac{-A_k}{m_k} \left[\Theta_{t-1,k} - \left(\Theta_t^0 - \eta_k \frac{d_{k,t}(\lambda)}{A_k} \right) \right] \quad \forall t \in T, k \in K_{ra} \quad (5)$$

$$\underline{\Theta}_k \leq \Theta_{t,k} \leq \bar{\Theta}_k \quad \forall t \in T, k \in K_{ra} \quad (6)$$

where $d_{k,t}(\lambda)$ represents the demand bids of the refrigeration appliances, which are estimated based on the temperature flexibility and can be expressed as:

$$d_{k,t}(\lambda) = \begin{cases} P_k^{ra} & \forall \lambda \leq f_{t,k}, t \in T, k \in K_{ra} \\ 0 & \forall \lambda > f_{t,k}, t \in T, k \in K_{ra} \end{cases} \quad (7)$$

where the temperature flexibility is estimated from the internal temperature and the threshold values as:

$$f_{t,k} = \frac{\Theta_{t,k} - \underline{\Theta}_k}{\bar{\Theta}_k - \underline{\Theta}_k} \quad \forall t \in T, k \in K_{ra} \quad (8)$$

3.3.2. Space heating or cooling appliances

For the operation of thermostat-controlled space heating or cooling (SHC) appliances (e.g. HP or HVAC), the building is considered as an isothermal mass of air with a volume specified by the building dimensions. The SHC appliances supply the heating or cooling demand to user-specified temperature set-points. The thermal equilibrium equation for the building can be written as:

$$\rho V C_B \frac{\partial \theta_t}{\partial t} = Q_t^{int} + Q_t^{ex} + Q_t^{gen} \quad \forall t \in T \quad (9)$$

where the internally generated heat (Q_t^{int}) represents the heat contribution of the building inhabitants and other heat-generating household devices. On the other hand, the heat exchanges through

the building surfaces (Q^{ex}) and the heat generation of the SHC appliances (Q^{gen}) can be written as:

$$Q_t^{ex} = \alpha(\theta_t^{out} - \theta_t) \quad \forall t \in T \quad (10)$$

$$Q_t^{gen} = \sum_{k \in K_{shc}} \gamma_k d_{t,k}(\lambda^*) \quad \forall t \in T \quad (11)$$

where $d_{t,k}(\lambda^*)$ indicates the power consumption of the SHC appliances at the equilibrium price λ^* .

The operational cost of SHC appliances to satisfy the heating or cooling demand can be calculated as:

$$C_t = \sum_{k \in K_{shc}} \lambda d_{t,k}(\lambda) \Delta t \quad \forall t \in T \quad (12)$$

For flexible operation, the indoor temperature is allowed to be flexible around the desired temperature set-point limited by $\theta_t \in [\underline{\theta}, \bar{\theta}]$ and the thermal discomfort of the consumer is represented as:

$$D_t = \beta |\theta_t - \theta_t^{set}|^2 \quad \forall t \in T \quad (13)$$

Therefore, the bidding strategy for SHC appliances can be formulated as a multi-objective optimization problem as in Eq. (14) to minimize operational cost and thermal discomfort.

$$\begin{aligned} \min_{d_{t,k}(\lambda)} \quad & [C_t \quad D_t] \quad \forall t \in T, k \in K_{shc} \\ \text{s.t.} \quad & \rho V C_B \frac{\partial \theta_t}{\partial t} = Q_t^{int} + \alpha(\theta_t^{out} - \theta_t) + \sum_{k \in K_{shc}} \gamma_k d_{t,k}(\lambda) \quad \forall t \in T \\ & d_{t,k} \in [0, \overline{P_k^{shc}}], \theta_t \in [\underline{\theta}, \bar{\theta}] \end{aligned} \quad (14)$$

As indicated in Eq. (15), the DA determines the optimal bid from the pareto-front of Eq. (14) according to a trade-off between two objectives specified by comfort index of the user. The comfort index represents the consumer's degree of willingness to sacrifice thermal comfort for financial saving, and expressed as in Eq. (16).

$$d_{k,t}(\lambda) = \begin{cases} d(\lambda)|_{\min(C_t^*)} & \forall \lambda > \phi_t, t \in T, k \in K_{shc} \\ d(\lambda)|_{\min(D_t^*)} & \forall \lambda \leq \phi_t, t \in T, k \in K_{shc} \end{cases} \quad (15)$$

$$\phi_t = \frac{|\theta_{t-1} - \theta_t^{set}|}{\bar{\theta} - \underline{\theta}} \lambda_{max} \quad \forall t \in T \quad (16)$$

Here, C_t^* and D_t^* represent the Pareto-front solutions of Eq. (14). The use of a comfort index ensures that, when indoor temperature deviates further from the desired set point, then the bid generation is comfort dominant, as the bid is selected from the Pareto-front that represents minimum thermal discomfort.

3.4. Buffer devices

Residential electrical-storage units such as battery-energy-storage systems (BESS) and EV batteries are considered as buffer devices. Their DAs generate bids to charge or discharge them according to operational constraints and user preferences. The bid of buffer DA is expressed as:

$$d_{k,t}(\lambda) = \begin{cases} P_k^{ch} & \forall \lambda \leq f_{t,k}, t \in T, k \in K_{bd} \\ P_{k,h}^{dis} & \forall \lambda > f_{t,k}, t \in T, k \in K_{bd} \end{cases} \quad (17)$$

where the flexibility of a buffer device depends on its current state of charge (SoC) and allowed SoC range as specified in the following equations:

$$f_{t,k} = \frac{\overline{\sigma}_k - \sigma_{t,k}}{\overline{\sigma}_k - \underline{\sigma}_k} \lambda_{max} \quad \forall t \in T, k \in K_{bd} \quad (18)$$

$$\underline{\sigma}_k \leq \sigma_{t,k}(\lambda) \leq \overline{\sigma}_k \quad \forall t \in T, \lambda \in \{0, 1\}, k \in K_{bd} \quad (19)$$

$$\sigma_{t,k}(\lambda) = \sigma_{t-1,k} + \frac{\eta_{t,k} d_{t,k}(\lambda) \cdot \Delta t}{E_k^{cap}} \quad \forall t \in T, \lambda \in \{0, 1\}, k \in K_{bd} \quad (20)$$

where $\eta_{t,k}$ represents the efficiency of the buffer device in terms of charging and discharging, which can be written as:

$$\eta_{t,k} = \begin{cases} \eta_k^{ch} & \text{when charging} \\ 1/\eta_k^{dis} & \text{when discharging} \end{cases} \quad (21)$$

Buffer device would be considered inelastic during the periods when the consumer wants to ensure its operation irrespective of its flexibility (for example-consumer might want EV must charge at any particular time). In addition to that, consumers' expected SoC level is ensured by setting following constraint for the buffer devices so that the corresponding buffer device is charged at least user-specified level (σ_k^{tar}) before by a specific time ($t = T_k^{tar}$):

$$\sigma_{t,k}(\lambda) \geq \sigma_k^{tar} \quad \forall k \in K_{bd}, t = T_k^{tar}, \lambda \in \{0, 1\} \quad (22)$$

This represents situations when a particular user wants any buffer device to be charged up to a certain level before any specific time (examples include situations when any user wants a specific SoC level of EV battery before departing home in the morning).

4. Grid support functions of HEMS

The methodologies for power grid support of HEMS can be subdivided into the functionality for congestion management and local voltage-violation support, which are discussed in the following sections.

4.1. Congestion management

In this paper, a DLC method is adopted for the congestion management based on active power curtailment, which operates in discrete time steps. Upon detection of congestion at any congestion points (main feeders or transformers), the network agent sends a curtailment request to the HEMS, indicating the power curtailment requirement, P^{curt} for the next time interval. Subsequently, the HEMS takes independent curtailment decisions based on the following steps:

- **Step 1:** The HEMS calculates the instantaneous power consumption, P_t^{total} in the house from the DA bids as:

$$P_t^{total} = \sum_{k \in K} d_{t,k}(\lambda^*) \quad \forall t \in T \quad (23)$$

where the power supplies from DERs are represented by negative values.

- **Step 2:** The priority index of each residential device, $x_{t,k}$ is calculated from the DA bids. This index represents the order of importance of a particular device if interruption of the device is required for DLC. Inelastic devices are always set as maximum priority, therefore $x_{t,k} = 0$ for $k \in K_{id}$. The priority indices for thermal devices depend on the non-zero values in their corresponding bids as shown in Eq. (24). Additional conditions for the operating cycles are included when determining priorities of the shiftable devices (as shown in Eq. (25)) to prevent interruption during operation as it can lead to financial and energy loss [4,25].

$$x_{t,k} = \sum_{\lambda=0}^1 z_{t,k}(\lambda) \quad \forall t \in T, k \in K_{td} \quad \text{where: } z_{t,k}(\lambda) = \begin{cases} 1 & \forall d_{t,k}(\lambda) = 0 \\ 0 & \forall d_{t,k}(\lambda) \neq 0 \end{cases} \quad (24)$$

$$x_{t,k} = \begin{cases} \sum_{\lambda=0}^1 z_{t,k}(\lambda) & \forall t \in T, k \in K_{sd}, c < 1, \quad \text{where: } z_{t,k}(\lambda) = \begin{cases} 1 & \forall d_{t,k}(\lambda) = 0 \\ 0 & \forall d_{t,k}(\lambda) \neq 0 \end{cases} \\ 0 & \forall c \geq 1 \end{cases} \quad (25)$$

On the other hand, as the buffer devices' priorities are estimated from the user preferences in terms of usage or SoC requirements. For example, users might want specific charge levels for the EVs before departing home. Such an SoC requirements are represented by a target SoC (σ_k^{tar}) and a target time (t_k^{tar}). Based on such requirements, their priority indices are calculated as:

$$x_{t,k \in K_{bd}} = \begin{cases} x_{max} & \forall \sigma_k^{tar} = \emptyset \\ \frac{\Delta \sigma_{t,k}^{gain}}{\Delta \sigma_{t,k}^{def}} x_{max} & \forall \sigma_k^{def} \neq \emptyset, \Delta \sigma_{t,k}^{gain} \geq \Delta \sigma_{t,k}^{def} \\ 0 & \forall \sigma_k^{def} \neq \emptyset, \Delta \sigma_{t,k}^{gain} \leq \Delta \sigma_{t,k}^{def} \end{cases} \quad (26)$$

where $\sigma_k^{tar} = \emptyset$ indicates that there are no SoC requirements, hence the priority index is x_{max} , which represents lowest priority. However, when there are SoC requirements, then the priority indices are calculated based on the target SoC deficiency, $\Delta \sigma_{t,k}^{def}$ and maximum SoC gain, $\Delta \sigma_{t,k}^{gain}$ by t_k^{tar} . The target SoC deficiency and SoC gain are calculated as:

$$\Delta \sigma_{t,k}^{def} = \sigma_k^{tar} - \sigma_{t,k} \quad \forall t \in T, k \in K_{bd} \quad (27)$$

$$\Delta \sigma_{t,k}^{gain} = \frac{P_k^{ch}(t_k^{tar} - t) \Delta t}{E_k^{cap}} \quad \forall t \in T, k \in K_{bd} \quad (28)$$

- **Step 3:** Once the priority indices are calculated, the HEMS sends curtailment signals to the respective devices for which the priority is the lowest (i.e. maximum priority index). The process continues until the curtailment request is satisfied as presented in Algorithm 1.

Algorithm 1

Power curtailment algorithm of HEMS for congestion management

```

1:  $t, k \leftarrow$  Time periods, devices
2: for all  $t$  do
3:    $P_t^{curt} \leftarrow$  HEMS receive power curtailment request from network agent
4:    $P_t^{total} \leftarrow$  Estimated total power consumption of the house
5:    $x_k \leftarrow$  Priority index of devices
6:   while  $P_t^{curt} \geq 0$  do
7:      $k^* \leftarrow \max(x_k)$ 
8:      $P_t^{curt} = P_t^{total} - P_{k^*}$ 
9:     Send switching signal to  $k^*$ 
10:     $K \leftarrow K - k^*$ 
11:   end while
12: end for

```

4.2. Local voltage-violation support

The node voltages of LV networks depend on the power flows

and the line impedances. Therefore, the voltage at node j for a typical N-bus radial feeder as shown in Fig. 3 can be written as:

$$v_{j,t} = v_{i,t} - \frac{r_{ij}P_{ij,t} + x_{ij}Q_{ij,t}}{v_{i,t}} \quad \forall t \quad (29)$$

where line flows $P_{ij,t}$ and $Q_{ij,t}$ are calculated from the power consumption at each nodes and the line impedances for the segment $i - j$ are represented by r_{ij} and x_{ij} .

The following sections discuss the proposed voltage control methodologies of the HEMS to maintain the voltage level at the POC of a house within the acceptable margin.

4.2.1. Under-voltage control

Under-voltage problems usually occur when the load in a radial LV feeder gets high and the voltage drops below minimum threshold. Therefore, the same DLC methodology of congestion management is adopted for under-voltage control (shown in Algorithm 2), where curtailment is activated when the voltage at the POC of the house drops below a lower threshold level, V_{lth} . The active power curtailment for under-voltage control is calculated as:

$$\Delta P_t^{uv} = P_t^{total} - P_t^m|_{V_{j,t}=V_{lth}} \quad (30)$$

where the maximum active power P^m to maintain the voltage above the threshold level is estimated from Eq. (29). The line flows and reactive power can be expressed as:

$$P_{ij,t} = P_{j,t} + P_{jk,t} \quad \forall t \in T \quad (31)$$

$$Q_{ij,t} = Q_{j,t} + Q_{jk,t} \quad \forall t \in T \quad (32)$$

$$Q = P \sqrt{\frac{1 - pf}{pf}} \quad (33)$$

Algorithm 2

Power curtailment algorithm of HEMS for under-voltage control

```

1:  $t, k \leftarrow$  Time periods, devices
2: for all  $t$  do
3:    $\Delta P_t^{uv} \leftarrow$  Equations (30) to (33)
4:    $P_t^{total} \leftarrow$  Estimated total power consumption of the house
5:    $x_k \leftarrow$  Priority index of devices
6:   while  $\Delta P_t^{uv} \geq 0$  do
7:      $k^* \leftarrow \max(x_k)$ 
8:      $\Delta P_t^{uv} = \Delta P_t^{uv} - P_{k^*}$ 
9:     Send switching signal to  $k^*$ 
10:     $K \leftarrow K - k^*$ 
11:   end while
12: end for

```

Contrary to other devices, the HP is considered to be subdivided into two loads, a pump load for heat-transfer and a resistive-heater that is used when the internal temperature drops significantly [39]. Both heating elements are separately considered for DLC when the HP is selected for curtailment based its x . The step control method of [24] is used to switch off the resistive-heater load (P_{heater}) separately when the voltage drops below the lower threshold V_{lth} . The HP is completely switched off in case the voltage drops lower than the lower boundary of acceptable level, V_{lb} (typically set at 0.9 p.u.). The above-mentioned relationship can be mathematically presented as:

$$P_{HP} = \begin{cases} P'_{HP} & \forall V_j \geq V_{lth} \\ P_{pump} & \forall V_{lth} > V_j \geq V_{lb} \\ 0 & \forall V_{lth} > V_j \geq V_{lb} \\ & \& P'_{HP} = P_{heater} + P_{pump} \\ 0 & \forall V_j < V_{lb} \\ & \& P'_{HP} = P_{pump} \end{cases} \quad (34)$$

where P_{HP} is the actual power consumption of HP and P'_{HP} denotes the power demanded by the HP device agent.

4.2.2. Over-voltage control

Residential DG units need to follow certain curtailment mechanisms in order to mitigate over-voltage at the POC. The well-known droop-control method [24,40] is adopted to manage the power injection at the POC. The droop-control is activated when the voltage at the connection point V_j exceeds the upper threshold voltage level of V_{uth} . The injected active power P_{inj} is curtailed following a linear function depicted by Eq. (35), and it is set to 0 when the voltage exceeds the maximum allowable limit of V_{ub} , which is typically set at 1.1 p.u. in the distribution networks.

$$P_{inj} = \begin{cases} P_{MPP} & \forall V_j \leq V_{uth} \\ P_{MPP} \left(1 - \frac{V_j - V_{uth}}{V_{ub} - V_{uth}}\right) & \forall V_{uth} < V_j \leq V_{ub} \\ 0 & \forall V_j > V_{ub} \end{cases} \quad (35)$$

where P_{MPP} denotes the maximum power point of the DG unit (e.g. PV system).

5. Simulation and results

The following sections discuss the case studies performed to assess the performance of the proposed methodology for grid support services and associated comfort reservation of the consumers.

5.1. Simulation setup

The proposed approach is investigated through simulations on a 0.4 kV (phase-to-phase) typical Dutch LV radial feeder supplying 42 households as illustrated in Fig. 4.

In addition to the inelastic loads and rooftop solar-PV system, four controllable devices are considered, namely freezer, washing machine, dishwasher, and heat-pump, along with an electric-vehicle battery. The buildings are considered as semi-detached Dutch houses (100–200 m²), for which the inelastic load profiles are generated from Ref. [41] considering an average annual energy demand of 3400 kWh per household. The nominal rated values of different household devices are shown in Table 1. For the operation of the freezer, m_k , A_k , and η_k are considered as 4.2×10^4 J/°C, 1.06 W/C, and 1.67 respectively, while the internal temperature is considered flexible between -19°C and -22°C . For the thermal model of buildings, the air mass density and thermal mass are considered as 1.2 kg/m³ and 1000 J/kg°C respectively. A flexible range between 22°C and 27°C is considered for the indoor temperature. A 90% round-trip efficiency is considered for the buffer devices ($\eta^{ch} = \eta^{dis} \approx 95\%$), whereas the maximum and minimum threshold values for SoC are considered as 90% and 10% respectively for all buffer devices.

The household appliances are modeled in MATLAB. The Pareto-front of Eq. (14) is solved using genetic algorithm in MATLAB. The simulations are run for two consecutive summer and winter days separately with the solar irradiation and temperature profiles as illustrated by Fig. 5. Generated bid curves from DAs are sent to the aggregator via HEMSs, and it calculates the equilibrium price λ^* for the cluster during each simulation interval of 15 min.

The lower and upper thresholds (V_{lth} and V_{uth}) of the local voltage control are set at 0.95 p.u. and 1.05 p.u. respectively, whereas V_{lb} and V_{ub} are set at 0.9 p.u. and 1.1 p.u. respectively. To observe the efficacy of the HEMS in grid support, two distinct cases are investigated. For Case I, 50% of the HEMSs in the network participate in grid support, while Case II considers support from the HEMSs of all the households.

The total feeder load in each time step of 15 min is estimated from the aggregated bid, and a curtailment request is prepared for the households that participate in grid support. The curtailment amount for each house P^{curt} is determined by uniformly distributing it among the set of participating houses (H), i.e:

$$P^{curt} = \frac{S_t - S_{thr}}{n(H)} \quad \forall S_t > S_{thr} \quad (36)$$

where S_t is the feeder load at time t and its maximum threshold (S_{thr}) is assumed to be 100 kVA for the analyses.

Fig. 3. Schematic diagram of N-bus radial feeder.

Fig. 4. One-line representation of the test feeder used in simulation.

Table 1
Nominal device ratings.

Device	Rated power/Energy
Washing machine	1500–2200 W
Dishwasher	1500–2000 W
Freezer	150–500 W
Heat pump	1500–3000 W
Solar PV	1500–4000 W _{peak}
Electric vehicle	18–30 kWh

The local voltage-control method is implemented at discrete time intervals of 1 min. Thus, the voltage level and appliance priority of one step are used to decide the actions to be taken in the next minute.

5.2. Simulation results for grid support

5.2.1. Summer

The higher solar irradiation and lower domestic load in summer results in a surplus of generated PV power. The surplus active power is injected into the feeder and results in a reverse flow of power, as shown in Fig. 6. Consequently, voltage levels rise along the feeder and violate the upper threshold value of 1.05 p.u. at a number of POCs. A histogram of the frequencies of the voltage levels in all the POCs is shown in Fig. 7. The number of upper threshold violations is largely reduced when the HEMS activates the droop control for the active power curtailment. The voltage profile at the last POC during the simulated days is shown in Fig. 8. When all the HEMSs of the feeder participate in grid support, a better voltage profile is achieved.

Key performance indicators are summarized in Table 2 for the summer simulation cases. The average household consumption is negative in all the cases due to a large amount of energy injected by

the PV systems. The amount of curtailed energy is reduced for the last POC when all the HEMSs in the feeder participate in grid support. This is due to the participation of more POCs in curtailment upon violation of the voltage limits. This is also reflected in the higher amount of total curtailment in the feeder.

5.2.2. Winter

Unlike the case in summer, the local generation is low in winter due to the relatively shorter length of the day and the reduced solar irradiation. A higher residential heating demand leads to an increased feeder load as well. As shown by the feeder load in Fig. 9, the threshold level of 100 kVA is violated during the evening of the first day. The HEMSs at the participating POCs respond to the curtailment request sent by the network agent by switching off suitable appliances. Consequently, the resulting feeder loads in both of the controlled cases remain within the threshold.

The histogram of the frequencies of the voltage levels in the feeder is shown in Fig. 10. A significant reduction in the lower threshold violation is observed when all the POCs are considered in grid support. It is important to note that the HEMS reacts after a violation is detected and implements the curtailment in the next time step. For instance, the voltage levels at the last POC during the simulated winter days are shown in Fig. 11. Local voltage control is triggered after the voltage level drops below 0.95 p.u. This is why the number of lower threshold violations is reduced, but cannot be completely nullified.

Like for the summer days, the performance indicators are tabulated in Table 3. The controlled cases prevent the thermal limit violations efficiently, as the HEMS responds to the curtailment request sent by the network agent. The average consumption is hardly affected, since the curtailed loads are supplied later. Due to the relatively lower PV generation, the voltage levels do not rise beyond the upper threshold. Thus, the curtailment of PV injection is not required.

Fig. 5. Global irradiation and outdoor temperature profiles used in the simulation.

5.3. Consumers' comfort reservation of HEMS

This section discusses the performance of the proposed HEMS in

Fig. 6. Total feeder load during the simulated summer days.

Fig. 7. Histogram of voltage levels during the simulated summer days.

Fig. 8. Voltage profile at the last POC during the simulated summer days.

Table 2
Simulation results for the summer days.

Indicator	No control	Case I	Case II
Max. load (kW)	103.32	93.1	92.25
Max. voltage (p.u.)	1.073	1.068	1.062
Min. voltage (p.u.)	0.951	0.951	0.951
Loading threshold violation (#)	15	0	0
Voltage threshold violation (#)	4845	2630	1384
Average daily household consumption (kWh)	-3.00	-1.64	-1.56
Curtailed PV injection (kWh)	0	55.01	68.5
Curtailed PV injection at the last POC (kWh)	0	4.26	3.27

Fig. 9. Total feeder load during simulated winter days.

terms of consumers' comfort and preferences reservation while switching different building loads or DERs for the congestion management or local voltage support.

- **Shiftable device:** The power profiles of shiftable devices for a selected house are presented in Fig. 12 for 24 h. The consumer

Fig. 10. Histogram of voltage levels during the simulated winter days.

wants to complete their operation of washing machine and dishwasher between hours 12–20. Two DLC instances are shown in the figure. The corresponding bid curves and priority indices of both shiftable devices are also highlighted. During the first DLC instance, the dishwasher has not been selected for curtailment due to its highest priority ($x = 0$). On the other hand, the washing-machine is selected for DLC during the second instance due to its higher value of x . Therefore, it is deferred to another period to satisfy the grid constraint. Nonetheless, it completes its full operation cycles within desired operation window.

- **Thermal device:** A selected freezer profile is shown in Fig. 13 for 24 h with associated temperature profile. A few DLC instances are also highlighted in the figure. The freezer consumption is not curtailed for the first DLC instance as it would violate the temperature constraint (highlighted in the figure). However, during the second DLC instance, it is selected for power curtailment due to its temperature flexibility, and it is switched-off to maintain the grid constraint.

A selected HP consumption profile is shown in Fig. 14 for a winter afternoon and associated temperature variations are also highlighted. It can be seen that the indoor temperature does not deviate further from the temperature set-points to minimize discomfort. Two DLC instances are highlighted in the figure to represent the effectiveness of the HEMS in comfort reservation for the consumer while operating in grid support mode. During the first DLC event, both the heater and pumps of HP are curtailed according to Eq. (34) whereas only the HP heater is switched off in the second DLC event. However, in both cases, the temperature constraints have been maintained.

- **Buffer device:** A selected EV charge-discharge profile is shown in Fig. 15 for 24 h with associated SoC profile and DLC instances. The periods when the EV is away are also highlighted in the figure. The nominal charge and discharge powers for this EV is considered as 3 kW with the maximum battery capacity as

Fig. 11. Voltage profile at the last POC during the simulated winter days.

Table 3
Simulation results for the winter days.

Indicator	No control	Case I	Case II
Max. load (kW)	106.63	98.91	99.66
Max. voltage (p.u.)	0.999	0.999	0.999
Min. voltage (p.u.)	0.937	0.94	0.94
Loading threshold violation (#)	30	0	0
Voltage threshold violation (#)	1755	834	706
Average daily household consumption (kWh)	28.56	28.5	28.5
Curtailed PV injection (kWh)	0	0	0

Fig. 12. Shiftable load profile of a selected house.

29.8 kWh, while the values for initial SoC at hour 0 and the SoC at arrival during hour 19 are arbitrarily considered as 50.3% and 54.5% respectively. It can be seen that, the HEMS satisfies all the SoC constraints of EV as discussed in Section 3.4 including the expected SoC level before departing home, which is considered as 70% (20.86 kWh) and the SoC level at departure is found to be 70.3% (20.95 kWh). Besides, the effect of DLC on EV schedules are also shown for 2 DLC events. EV charging is deferred to provide grid support during the first DLC period as $\Delta\sigma_{t,k}^{gain} \geq \Delta\sigma_{t,k}^{def}$. However, EV charging is not curtailed for the second DLC event because of its higher priority at that time (as $\Delta\sigma_{t,k}^{gain} < \Delta\sigma_{t,k}^{def}$). Therefore, consumers' preferences are always satisfied by the proposed methodology even when carrying out DLC scheme for grid support.

6. Experimental validation

The following sections discuss the developed experimental prototype of the proposed HEMS and its performance verification in practical environment.

6.1. Laboratory setup

The laboratory test setup and the associated communication among the agents and devices are illustrated in Figs. 16 and 17

Fig. 13. Freezer load profile of a selected house.

Fig. 14. Heat-pump profile of a selected house.

Fig. 15. EV power and SoC profile of a selected house.

Fig. 16. Single-line representation of the laboratory test setup.

respectively. A California Instrument programmable power source, MX45, supplies the test feeder. The test feeder is equipped with a SATEC EM133 smart meter, which offers real-time data acquisition through TCP/IP communication. A household POC is used in the tests, located approximately 150 m away from the source. The test house is considered to be equipped with a freezer, a HP and a PV unit. Software models of a freezer and an HP are developed in Simulink representing the thermal characteristics of the devices. The multi-objective optimization model for bid generation is converted into a standalone executable using Simulink model. The Simulink models are used in combination with the software agents embedded in the Raspberry Pi. As shown in Fig. 17, a feeder agent and a device agent are used along with an HEMS agent, where the feeder agent represents the network agent or DSO. The agents are realized using Raspberry Pi 3, which can access the home-area network (HAN) via TCP/IP communication. The Raspberry Pi 3 is equipped with a 1.2 GHz 64-bit quad-core Central Processing Unit (CPU) and 1 GB of Random Access Memory (RAM). Due to its low

cost and reliable computational capacity, Raspberry Pi has been extensively used in numerous automation projects worldwide. In addition to that, MATLAB support package for Raspberry Pi and MATLAB Coder allows the standalone executable Simulink models to directly run on Raspberry Pi, which are used for bid function generation of device agents.

As discussed in Section 4.2.1, the HP load is considered to be divided into two parts, P_{pump} and P_{heater} . Three fixed loads are used to represent the power consumption of the freezer (P_{fr}) and the two heating loads of the HP. The nominal ratings of the loads are shown in Table 4. The loads are connected to the main supply via Pikkerton ZBS-110V2 smart plugs. Apart from gathering the consumption data, the smart plugs are also capable of switching the connected appliances on or off following remote signals using the ZigBee communication protocol. The smart plugs are coordinated by a ZigBee gateway that works as the interface between the smart plugs and the agent environment.

A 1.5 kW manually controllable resistive load is connected at the POC to emulate the uncontrollable base loads. A MasterVolt PV inverter with a nominal rating of 3 kWp is used in the tests. A PV simulator is coupled with the inverter that emulates the DC output of the PV panels. A resistive load with a nominal capacity of 10 kW is connected at the beginning of the feeder, that represents the aggregated network load. Voltage levels are expressed in p.u. values, considering a nominal line-to-neutral voltage of 230 V.

For the sake of simplicity, the communication between the feeder agent and the HEMS is activated every 30 min, whereas the local voltage control takes place once every 3 min.

6.2. Experimental results

In order to test the under-voltage control methodology, the voltage at the POC needs to be lower than a certain threshold. Given the short length of the test feeder and the light loading condition, the under-voltage problems are generated by setting the supply

Fig. 17. Communication among the agents and the smart plugs.

Table 4

Rated values of the loads used in the experimental setup.

Load type	Rating
Base load	1.0 kW
Freezer (P_{fr})	500 W
HP resistive heater (P_{heater})	1.5 kW
HP pump power (P_{pump})	1.0 kW
PV system	3 kWp
Rest of the network	10 kW

voltage V_s at 0.96 p.u. The local control is activated when the voltage at the POC V_r reaches 0.955 p.u. Similarly, a threshold loading level of 14 kW is considered to test the power curtailment functionality of the HEMS for congestion management.

The values of V_r are measured by taking the average of the voltage values read by the smart plugs. Fig. 18 depicts the voltage levels at the POC for both controlled and uncontrolled cases, while the measured power consumptions of the devices are shown in Fig. 19. The voltage at the POC reaches 0.9537 p.u. at 07:00 h in the morning. The HEMS agent implemented on the Raspberry Pi identifies the freezer as the least preferred device at this moment according to the methodology discussed in Fig. 4. It sends the switching message to the DA of the freezer, which is also implemented on Raspberry Pi. The freezer DA then sends the switching signal to the smart plugs to which the freezer is connected and the plug automatically limits power supply to the freezer without human intervention. As a result, the freezer is switched off (as shown in Fig. 19) to recover the voltage level, whereas the HP is operating with both heating elements, as the HP was on high priority due to the low indoor temperature of the house at that time. However, the resistive heater is switched off after 30 min and the voltage level improves to 0.9574 p.u. At this point, the freezer is switched back on, since the voltage threshold is no longer violated.

The total feeder load, as shown in Fig. 20, is measured by the EM133 smart meter, connected at the beginning of the test feeder. The feeder load reflects the switching actions of the devices to satisfy the voltage threshold. Additionally, the threshold of 14 kW is violated at 20:30 h. Since this higher load also violates the voltage threshold, the freezer is switched off to improve the voltage level. However, the resulting voltage and feeder loads still violate the corresponding thresholds. Thus, a curtailment request is sent by the feeder agent, and the resistive heater is identified as the least preferred load at that time by the HEMS agent and corresponding signal is sent to smart plug and it is switched off at 21:00 h. The resistive heater being the dominant load, the voltage improves significantly following the switching action.

Note that the voltage threshold violation occurring at 01:30 h could not be prevented by the HEMS. This is because neither of the two flexible devices could be switched off at this time without violating the minimum level of comfort. This indicates the importance of the number and diversity of the flexible loads that can be used for grid support. Additionally, the voltage violation could well have been prevented, had the support been provided by the HEMSs at the preceding POCs of the feeder.

7. Conclusion

In this paper, the application of HEMSs for grid support has been

Fig. 18. Measured voltage at the POC for the controlled and uncontrolled cases.

Fig. 19. Power consumption of the loads: (a) Uncontrolled case, (b) Controlled case. The numbers indicate the switching actions for the grid support.

Fig. 20. Measured feeder load for the controlled and uncontrolled cases.

investigated involving simulation analyses and laboratory demonstration tests. HEMS being the coordinator of residential energy management, is capable of performing switching actions to maintain various network requirements. To this end, a rule-based approach is devised that can complement market-oriented methods with direct control approaches, where the network support is provided by curtailing the active power injection/consumption via HEMS.

The proposed methodology is verified with case studies performed on a typical Dutch LV feeder. Results indicate that the proposed methodology can effectively mitigate overloading even with 50% participation of the HEMS for grid support. Improved voltage levels and a reduced energy curtailment are expected when all the HEMSs participate in grid support. However, the voltage levels strongly depend on the location of the participating HEMSs as the switching actions are taken based on the voltage values measured by the smart meter. Therefore, an HEMS located closer to the transformer will need to curtail a much lower amount of load compared to the one at the end of the feeder. Therefore, a more

advanced algorithm is warranted for local voltage control that enables a coordinated operation incorporating peer-to-peer communication. Simulation results also indicate the comfort and preferences reservation of the consumer in both normal and grid support operation modes of the HEMS. From grid operators' perspective such methodologies for congestion management are economically more viable than investing in grid reinforcement even if consumers' are incentivized for their flexibility support [4]. However, the optimal incentive structure needs to be developed to maximize profits both for the consumers and grid operators, which will be considered in future research by the authors.

A laboratory prototype of the proposed HEMS has been developed and tested in an experimental setup. The HEMS is embedded in a Raspberry Pi and controls the devices using an HAN. Smart plugs are used to measure the voltage levels and power consumption of devices as well as to remotely (dis)connect devices. The communication is realized through TCP/IP and ZigBee protocols. The prototype is tested for local under-voltage control and congestion management using three loads. Test results indicate a promising potential of the developed prototype. However, detailed insights are expected upon practical evaluation in a larger network involving diversified loads and switching possibilities.

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