Fair-Optimal Bi-Level Transactive Energy Management for Community of Microgrids

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***Abstract*—The inappropriate mechanism designs for demand response (DR) in the community of microgirds (CoMGs) may cause massive problems such as increase of the consumers' costs, rebound peaks and thereby lack of optimality in the network. In this paper, a bi-level energy management system is proposed to tackle the challenges associated with DR programs for CoMGs. The current structure successfully models users' behavior and dissatisfaction in the first level of optimization to develop best DR program for each of them. Moreover, in the second level, power system constraints are taken into account to prevent voltage and current deviation from their standard range. Each user is assumed to be part of a microgrid (MG) whose operation is controlled and optimized through its local energy management system (EMS) in the first level. On the other hand, the overall operation of all MGs is delegated to the whole system operator which acts as the central energy management system (CEMS) in the second level. An iterative transactive energy management method is proposed by CEMS to fairly limit the excess power of the MGs one day ahead for voltage and current regulation. The obtained results indicate the effectiveness of the proposed structure in preventing discomfort issues, voltage deviation and creation of the rebound peaks in the system.**

***Index Terms*—Demand response, energy management system, fair allocation, machine learning, user behavior.**

NOMENCLATURE

Sets

h	Number of houses
n	Number of microgrids (MG)
P	Number of trained outputs
r/j	Indices showing size of training weights matrix
t	Time
t_{st}	Desired start time of shiftable loads

Parameters

β_h^{hvac}	Overall desired day-ahead comfort level
$\overline{E}^{ES}/\underline{E}^{ES}$	Upper/lower electric storage level [kWh]
$\overline{P}^{ch}/\overline{P}^{dis}$	Maximum charging/discharging power of electric storage [kW]
$\overline{P}_{t,n}^{sell}/\underline{P}_{t,n}^{sell}$	Upper/lower limit of sold power [kW]
$\overline{v}/\underline{v}/v^r$	Maximum/minimum/rated wind speed of wind turbine [m/s]
π_t^e	Electricity price [$]
π^{ch}/π^{dis}	Price of charging/discharging electric storage [$/kWh]
π^{PV}/π^{WT}	Price of energy from photovoltaic system/ wind turbine [$/kWh]
ψ	Function for updating training weights during learning process
I^{max}/I^{min}	Maximum/minimum line current [A]
itr^{max}	Maximum number of iterations for training
m	Total number of MGs in allocation
P^r	Rated wind turbine power [kW]
$P_{t,h}^{Fhvac}$	Forecasted HVAC consumption [kW]
$P_{t,h}^{fixed}$	Fixed loads [kW]
P_t^{WT}/P_t^{PV}	Power generated by wind turbine/photovoltaic system [kW]
S	Set of generated coalitions
V^{max}/V^{min}	Maximum/minimum busbar voltage limit [p.u.]
v_t	Hourly wind speed [m/s]
α_h^{sh}	Dissatisfaction coefficient of shifting load [$/kWh]
η^{ch}/η^{dis}	Efficiency of charging/discharging electric storage [%]
η^{PV}	Efficiency of photovoltaic system [%]
$\lambda_{t,h}$	Hourly desired day-ahead comfort level
a^g	Micro-turbine constant term of cost function [$]
A^{PV}	Area of photovoltaic system [m^2]
b^g	Micro-turbine linear term of cost function [$/kW]
c^g	Micro-turbine quadratic term of cost function [$/(kW)^2]
G_t	Solar irradiance [w/m^2]

Variables

$\hat{y}_k/y_k$	Target/trained output
$d_{t,h}^{shift}/d_{t,h}^{hvac}$	Dissatisfaction cost of shiftable/HVAC loads [$]
E/MSE	Training error/mean squared error
E_t^{ES}	Electric storage level [kWh]
I^{np}	Binary variable showing wether x is positive or negative
$I_{line(i)}$	Current of line i [A]
I_t^{ch}/I_t^{dis}	Binary variables of charging/discharging state of electric storage
$P_{t,h}^{hvac}$	HVAC loads [kW]
$P_{t,h}^{Tsh}$	Total shiftable loads [kW]
$P_{t,n}^{RED}$	reduction in sold power [kW]

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$P^{shift}_{t,t_{st},h}$	Shifted power [kW]
P^{buy}_t/P^{sell}_t	Power bought from/sold to grid [kW]
P^{ch}_t/P^{dis}_t	Charging/discharging power of electric storage [kW]
P^{MT}_t	Power generated by micro-turbine [kW]
SU_t/SD_t	Startup/shutdown cost of micro-turbine [$]
V_t	Voltage of the busbar with maximum voltage [v]
$V_{bus(i)}$	Busbar voltage [p.u.]
$W_{k,j}$	Training weights
x^p/x^n	Positive/negative parts of x

I. Introduction

The increase in the penetration of distributed energy resources (DERs) has heightened the need for an energy management system focused on the intermittency of renewable generation and the application of demand-side management [1]. Demand response (DR) programs, as one of the most effective demand side management techniques, maintain demand and supply in balance [2], increase operational reliability [3] and provide other ancillary services [4].

Use of DR in peak electrical load hours will lead to lower energy costs [5] and prevent peaking power plants to generate power for satisfying demand [6]. Two of the major DR schemes are direct load control (DLC) and price-based control methods like Time of Use (TOU) programs [7]. DLC programs authorize the utility company control over registered loads during peak demand time while in TOU programs, consumers change electricity usage patterns in response to changes in the power price. The main drawbacks of DLC and TOU programs are loss of consumer comfort and creation of rebound peaks, respectively.

DR programs based on a cost-benefit structure could generate a new peak, as stated in [8], by shifting the demand to low cost periods in a community of microgrids (CoMGs). Various methods have been presented in literature to overcome this issue. To this end, a market-based coordination framework for residential thermostatically controlled loads (TCLs) is presented in [9, 10] to cap the aggregated peak consumption. Each TCL consists of a smart thermostat that is able to measure room temperature and submit bids to the system coordinator. A transactive coordination method is developed in [11], while considering aggregate model of DERs including TCLs. Optimal price signals are calculated through a model predictive control to achieve desired DER energy usage.

In [12], a dynamic energy management framework is presented to study the potential of the residential DRs. In order to handle the rebound peak effect, multi-time-of-use (multi-TOU) and multi-critical peak pricing (Multi-CPP) structures are used which are based on group pricing. A DR strategy for HVAC devices is proposed in [13] which minimizes comfort violation of the end users. In order to cope with development of rebound peaks, additional constraints have been introduced to the model to keep load factor greater than a predefined value. In [14], a dynamic nonlinear pricing mechanism for behind the meter DERs is developed which prevents creation of rebound peaks as well. Also, a sequential dispatch strategy for air conditioners is developed in [15] which aims to mitigate lead-lag rebound effect by dispatching grouped air conditioners in sequence. However, the following concerns are raised regarding the effectiveness of these methods:

- A large amount of data exchange between individual TCLs and the system coordinator is needed when TCL bidding is considered.
- Designing a fair and realistic pricing mechanism that takes the user comfort into account is a very complex problem. For example, a multi-TOU scheme which offers lower prices to a group of customers at 3 a.m. cannot be effective due to not considering user behavior and comfort.
- It is uncertain that how many of these strategies will work in practice when the complex interactions between customer behavior, technical and economic factors are considered [16].

However, energy management-based frameworks can be very beneficial in this regard, if they take user behavior uncertainty into account. Moreover, previous studies indicate only 10% of consumers participate in DR programs [8]. Therefore, residential customer behavior must be carefully examined to enhance energy management algorithms, model user's habitual consumption pattern and include user behavior in management methods.

Extensive research has been performed in the literature to present various energy management methods for MGs. To this end, a day-ahead centralized energy management strategy for CoMGs is formulated in [17] that minimizes operation cost. Heuristic Tabu Search algorithm is used to solve the optimal load flow problem. A transactive energy management framework is proposed by [18] to minimize cost and power mismatch in MGs which is solved using Artificial Bee Colony algorithm. An adaptive model-based horizon control technique is integrated into the energy management scheme in [19] to investigate the effects of the disturbance predictions. A semi-supervised spectral clustering-based approach is presented by [20] to control the power exchanges between islanded MGs via a VSC-HVdc link.

In [21], a bi-level energy management method is developed for CoMGs to minimize operation costs considering voltage constraints in system. The optimal power flow problem is simplified using Column and Constraint Generation method. Other objectives considered for the energy management of CoMGs include minimizing dissatisfaction, energy loss [22] and CO2 generation [23]. To the best of the author's knowledge, no previous study has developed an energy management method for CoMGs which takes the behavior of electricity consumers into account for demand response, reduces rebound peak effect, considers voltage and current constraints of the system, minimizes cost and consumer dissatisfaction in a fair manner simultaneously.

User behavior has been modeled in different ways in literature. A number of studies have used stochastic methods to consider user behavior uncertainty [24, 25]. HVAC consumption of a university building is modeled using simplified conduction heat transfer equations in [26]. Some studies have used simplified model of GridLAB-D simulator for modeling of thermal loads of a house [27]. An equivalent resistance-capacitance model is presented in [28] for modeling of HVAC loads. In [29], regression method is used to model energy consumption of houses. However, energy consumption of a real residential house is affected by many factors such as geographical location, weather, season, occupant habits and etc. Therefore, none of these methods can accurately estimate energy consumption of a household. Alternatively, a novel machine learning-based approach for modeling of HVAC consumption is developed in [30] to address these issues. However, the presented model is nonlinear and very complex. Moreover, it does not present a comprehensive modeling of the user's desired comfort level.

In this paper, a semi-centralized bi-level energy management scheme is proposed to overcome issues related to aggregated effect of DRs and DERs in the network. Machine learning approach is used to model the HVAC energy consumption of residential sector while considering the user's habitual energy consumption pattern and desired comfort level in the first level and it is coupled to a fair transactive energy management architecture in the second level to prevent voltage and current deviation in CoMGs. Doing so, the power system is able to minimize cost and user dissatisfaction and it can use the full potential of both DRs and DERs without causing rebound effect or voltage and current deviation in the system. In general, the main contributions of this paper are:

- Presenting a Leaky Rectified Linear Unit-based (Leaky ReLU-based) deep machine learning model for HVAC devices of residential sector which can be easily implemented as a mixed-integer linear model to the first-level optimization;
- Proposing a new transactive energy management scheme which fairly limits excess power of the MGs for sale to ensure voltage and current regulation, prevent rebound peaks and maintain user privacy in the second level.

The linear optimization model of the first level minimizes cost and user dissatisfaction. It is also fast and ensures reaching the global optima. None of the previous studies modeled the learned HVAC behavior as a linear formulation in the optimization of energy management of CoMGs. The learned HVAC model which was presented in the previous studies was nonlinear, very complex and difficult to implement. Thus, when integrated into the optimization model, the problem could only be solved using the heuristic methods. The heuristic methods are computationally inefficient and they often lead to local optimal solutions (that is; not global optimal). Further, the proposed transactive energy management algorithm in the second level is completely new. It employs a fair approach for voltage and current regulation, prevents rebound peak effect, has low computational burden and allows evading the nonlinear and non-convex optimal power flow problem.

II. Problem Formulation

To study the DR programs and their associated issues from both user and power system perspective, a bi-level energy management scheme is proposed. In the first level, by deploying machine learning techniques, local energy management system (EMS) of each MG models HVAC consumption of its consumers as a function of thermostat setting, indoor and outdoor temperature. Also, in this level each EMS schedules its load and resources to obtain maximum profit for the next day.

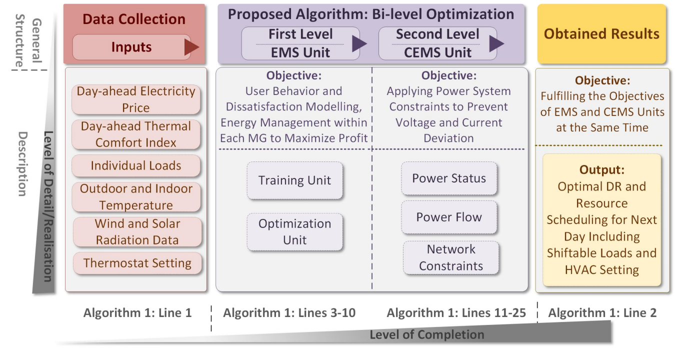


Fig. 1. System Structure.

In the second level, power system constraints are introduced by the central energy management system (CEMS) and an allocation-based transactive energy management method is designed here which allows the CEMS to fairly limit excess power of each MG for sale to regulate voltage of the busbars and current of the lines. Results of this level is then sent back to the first level as a feedback to allow the MG operators optimize their operation considering network limitations. The process runs iteratively until a stable operating point is reached. A general schematic of the aforementioned process is presented in Fig. 1.

The system under study is a CoMGs where each MG includes various renewable and non-renewable generation resources and multiple houses as loads. In general, the proposed generation units are micro-turbines, solar panels and wind turbines. Additionally, each MG has an energy storage unit as an inseparable part of renewable-based generation. Each house inside MGs has three types of loads which are fixed, shiftable and HVAC loads. Therefore, two different types of DR is used in this study: 1) shifting-based DR for shiftable loads and 2) learning-based DR for HVACs. The mathematical formulation of the aforementioned bi-level structure is presented in the following subsections.

A. EMS Formulation

Two tasks are performed by the EMS. First, supervised machine learning is used to obtain the mathematical model of the HVAC consumption of each house based on the data collected from smart meters and according to its user's behavior. This is achieved by providing one-week thermostat setting, indoor and outdoor temperature as inputs to a training unit while the HVAC energy consumption is the target.

The neural network structure, as shown in Fig. 2, is used to obtain the weights and the biases which model the target as a function of the inputs. By using the Leaky ReLU activation function, which is shown by $Y = F(X) = (f(X_1), f(X_2), f(X_3))$ in Fig. 2, the obtained HVAC model was simplified. Also, in this level, each user can independently determine its total and hourly desired comfort level for next day for HVAC loads.

Using Leaky ReLU as the activation function provides the following benefits for our model: 1) Leaky ReLU is a non-

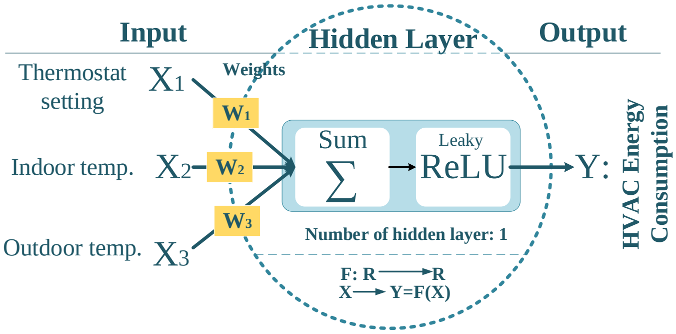


Fig. 2. Neural network structure to learn HVAC consumption behavior.

saturating activation function; 2) It does not suffer from the zero dying problem (in contrast to ReLU); 3) The model obtained by training using Leaky ReLU can be programmed as a mixed-integer linear optimization problem; 4) Leaky ReLU is fast and has lower Mean Squared Error (MSE) compared to other activation functions for this study.

One of the advantages of using machine learning instead of heat transfer equations or other methods is that learning-based models can easily adapt to changes in weather and season and they can get updated according to them. For example, in the proposed model, always the past one-week consumption, thermostat setting, indoor and outdoor temperature data is used for training the neural network. As the time passes and the weather and consumption change, the model for each house is updated and retrained using the new data.

Next, each EMS manages all of the MG resources and loads in a way to maximize MG utility which is composed of energy selling profit and user satisfaction. The objective function of this optimization problem is presented in (1). The first two terms are the cost of energy produced by dispatchable and non-dispatchable generation units and are calculated by (2) and (3), respectively. Equation (2) is approximated as a piecewise linear function similar to [31]. The third term shows the cost of trading energy with the main grid and is calculated by (4). The last term represents the dissatisfaction caused to the customers due to DR programs in the format of a financial loss and is calculated by (5) which consists of dissatisfaction caused due to the shifting of loads and dissatisfaction due to the scheduling of HVAC systems.

$$\min \sum_t \sum_h \left\{ \mathrm{C}_t^{MT} + \mathrm{C}_t^{NDU} + \mathrm{C}_t^{Grid} + \mathrm{C}_{t,h}^{DR} \right\}, \tag{1}$$

$$\mathrm{C}_t^{MT} = a^g + b^g P_t^{MT} + c^g {P_t^{MT}}^2 + SU_t + SD_t \ , \tag{2}$$

$$C_t^{NDU} = \pi^{PV} P_t^{PV} + \pi^{WT} P_t^{WT} + \pi^{ch} P_t^{ch} + \pi^{dis} P_t^{dis}, \tag{3}$$

$$\mathrm{C}_t^{Grid} = \pi_t^e P_t^{buy} - \pi_t^e P_t^{sell}, \tag{4}$$

$$\mathrm{C}_{t,h}^{DR} = d_{t,h}^{shift} + d_{t,h}^{hvac}. \tag{5}$$

1) Power Balance Constraint: Power balance constraint states that the summation of generated power should be equal to the consumption. This is shown by (6).

$$\begin{aligned} &P_t^{MT} + P_t^{PV} + P_t^{WT} + P_t^{dis} + P_t^{buy} \\ &= P_t^{ch}(t) + P_t^{sell} + \sum_h P_{t,h}^{fixed} + P_{t,h}^{hvac} + P_{t,h}^{Tsh}. \end{aligned} \tag{6}$$

2) Modeling Dissatisfaction: Dissatisfaction cost for changing the start time of shiftable loads is presented by (7). Equation (8) presents the dissatisfaction cost of scheduling HVAC loads. Both models have been adopted from [32]; however, (8) has been estimated as a piecewise linear function to reduce the burden in solving the current optimization problem. It is worth mentioning that human interaction is only needed in this part to determine the hourly desired comfort level for next day.

Dissatisfaction cost is added as a penalty cost to the objective function to involve customer's specific needs and desires for the next day. Considering the dissatisfaction cost is essential for obtaining more realistic results as it prevents the shifting of loads to undesirable hours and prevents the unreasonably lowering of the HVAC thermostat setting to decrease the energy consumption. For example, a customer may want to use a washing machine to get clothes ready at specific time, and if the operation of the machine is delayed, it will cause discomfort and dissatisfaction to the customer. Similarly, setting the thermostat of an HVAC system to minimum (to reduce energy consumption) will cause user's discomfort and dissatisfaction.

$$d_{t,h}^{shift} = \sum_{t_{st}} \alpha_h^{sh} \left| t_{st} - t \right| P_{t,t_{st},h}^{shift}, \tag{7}$$

$$d_{t,h}^{hvac} = \beta_h^{hvac} \{ P_{t,h}^{Fhvac} \pi_t^e [1 - (\frac{P_{t,h}^{hvac}}{P_{t,h}^{Fhvac}})^{\lambda_{t,h}}] \}. \tag{8}$$

3) Electric Storage: Equations (9) to (13) have been applied to model the operation of electrical storage. Equation (9) calculates storage level, (10) prevents overcharging of the storage, and (11) to (12) define the maximum charging and discharging rates of the storage. Moreover, (13) prevents the simultaneous charging and discharging of the storage.

In this study, to model battery degradation, a charging and discharging cost is assigned to each energy storage as shown by (3), [33]. This prevents the excessive charging and discharging of the storage which degrades the battery cells and reduces its lifetime. Moreover, overcharging or overdischarging of the storage can degrade the device and to prevent this (10) is used [34].

$$E_t^{ES} = E_{t-1}^{ES} + P_t^{ch} \eta^{ch} - P_t^{dis} \eta^{dis}, \tag{9}$$

$$\underline{E}^{ES} \le E_t^{ES} \le \overline{E}^{ES}, \tag{10}$$

$$0 \le P_t^{ch} \le \overline{P}^{ch} I_t^{ch}, \tag{11}$$

$$0 \le P_t^{dis} \le \overline{P}^{dis} I_t^{dis}, \tag{12}$$

$$0 \le I_t^{ch} + I_t^{dis} \le 1 \ . \tag{13}$$

4) Wind Turbine: The output power of the wind turbine is calculated by (14). The model has been extracted from [35].

$$P_t^{WT} = \begin{cases} 0 & \text{if } v_t \le \underline{v} \text{ } or \text{ } v_t > \overline{v} \\ \frac{v_t - \underline{v}}{v^r - \underline{v}} P^r & \text{if } \underline{v} \le v_t \le v^r \\ P^r & \text{if } v^r \le v_t \le \overline{v}. \end{cases} \tag{14}$$

5) Photovoltaic System: The produced power of the solar panels is calculated by a simple formulation as shown by (15) which takes photovoltaic system efficiency, area and solar irradiation into account.

$$P_t^{PV} = \eta^{PV} A^{PV} G_t. \tag{15}$$

6) Power Selling Constraint: Due to the voltage and current limitations that exist in the power system, MGs cannot sell as much power as they desire. Simultaneous power selling by all MGs can result in overvoltage or overcurrent issues in the system. Therefore, constraint (16) is introduced to the primary level after the first iteration of the optimization to limit the amount of excess power for sale by each MG. The value of $\overline{P}_t^{sell}$ is determined by the secondary level as an input to the next iteration of primary level.

$$0 \leq P_t^{sell} \leq \overline{P}_t^{sell}. \tag{16}$$

7) Leaky ReLU Linear Formulation: As it was mentioned earlier, one of the reasons for using Leaky ReLU activation function was its capability to be formulated as a mixed-integer linear model. Formulating the optimization problem as a mixed-integer linear model decreases the computational burden to solve the problem and it ensures reaching the global optimal solution. Leaky ReLU activation function (with a leak parameter value of 0.01) is defined as (17) and it can be reformulated as a linear model using (18) to (21). This type of formulation is called the big-M method where M is a very big number.

$$F(x) = \begin{cases} x & \text{if } x \geq 0 \\ 0.01x & \text{if } x < 0, \end{cases} \tag{17}$$

$$x = x^p - x^n, \tag{18}$$

$$0 \leq x^p < M \times (1 - I^{np}), \tag{19}$$

$$0 \leq x^n < M \times I^{np}, \tag{20}$$

$$F(x) = x^p - 0.01 \times x^n. \tag{21}$$

B. CEMS Formulation

In the second level, power system constraints are checked to ensure feasibility of the results obtained from the first level. Voltage and current stand as some of the main aspects of power system stability. Therefore, an iterative algorithm is applied here to prevent voltage and current deviation from their acceptable threshold. This algorithm fairly limits excess power of the MGs for selling in the next day using a transactive energy management scheme. The proposed method in this level is depicted in Algorithm 1.

As can be seen, after performing the first level of optimization for all of the MGs by EMS (lines 3-10); first, a power flow is performed by CEMS to determine the hours with voltage and current deviation problem. Next, for the hours with overvoltage problem, an initial guess (IG) for the total reduction of the excess power of all MGs of the system is provided.

Then, the share of each MG in increasing the voltage of the busbar with maximum overvoltage is determined using Shapley Value allocation method [36]. For this purpose, (22) is used. To demonstrate how the shares are calculated, the share of MG1 when three MGs have excess power is shown by (23).

$$Share_{t,n} = \sum_{S:n \notin S} \frac{|S|!(m-1-|S|)!}{m!}[V_t(S \cup \{n\}) - V_t(S)], \tag{22}$$

$$\begin{aligned} Share_{t,1} = & \frac{0! \times 2!}{3!}[V_t(\{MG1\}) - V_t(\{\emptyset\})] \\ & + \frac{1! \times 1!}{3!}[V_t(\{MG1, MG2\}) - V_t(\{MG2\})] \\ & + \frac{1! \times 1!}{3!}[V_t(\{MG1, MG3\}) - V_t(\{MG3\})] \\ & + \frac{2! \times 0!}{3!}[V_t(\{MG1, MG2, MG3\}) - V_t(\{MG2, MG3\})]. \end{aligned} \tag{23}$$

Algorithm 1: Bi-level Algorithm

1 **Input** int X= input ();
$X = \{x_n, \ n = [1, 2, .., 5]\}$ x_n=[day-ahead energy price, thermal comfort index, individual loads, temperature, wind data, thermostat setting]
2 **Output:** Y=[Optimal DR and resource scheduling for next day including shiftable loads and HVAC setting]
Algorithm I: EMS Unit (First Level)
3 **for** $\forall n \in \{1, 2, ..., 5\}$ **do**
4 **for** $\forall h \in \{1, 2, 3, ...\}$ **do**
▷ Training Unit: training data (70%) and validation data (30%)
5 Initialize $W = [W_{r,j}], \forall r, j \in \{1, 2, 3\}$;
6 **while** $MSE = \frac{1}{P}\sum_{k=1}^{P}(\hat{y}_k - y_k)^2 > \varepsilon \ \| \ itr < itr^{max}$ **do**
7 **for** $\forall r, j$ **do**
8 $W_{r,j} = W_{r,j} - \psi(\frac{\partial E}{\partial W_{r,j}})$;
9 $itr = itr + 1$
▷ Optimization unit
10 Minimize (1) considering the constraints (6) to (16) for each MG;
Algorithm II: CEMS Unit (Second Level)
11 **for** $1 \leq t \leq 24$ **do**
12 Calculate $P_{t,n}^{sell}$;
13 Do power flow;
▷ Determining hours with voltage deviation
14 **while** $V_{bus(i)} > V^{max} \ \| \ V_{bus(i)} < V^{min} \ \| \ I_{line(i)} > I^{max} \ \| \ I_{line(i)} < I^{min}$ **do**
15 $flag = 1$;
▷ Calculating MG shares in causing voltage deviation problem
16 **while** $P_{t,n}^{sell} > \underline{P}_{t,n}^{sell}$ $, \forall MG_n$ **do**
17 Do allocation for MGs that fulfill previous condition;
18 Calculate $P_{t,n}^{RED}$;
▷ reducing power sale of MGs proportional to shares and checking if voltage deviation problem is solved
19 **while** $P_{t,n}^{sell} > P_{t,n}^{RED}$ **do**
20 Calculate $\overline{P}_{t,n}^{sell}$;
21 Do power flow with $\overline{P}_{t,n}^{sell}$;
22 **if** $V_{bus(i)} < V^{max}$ & $V_{bus(i)} > V^{min}$ & $I_{line(i)} < I^{max}$ & $I_{line(i)} > I^{min}$ **then**
23 $P_{t,n}^{sell}$ upper bound is $\overline{P}_{t,n}^{sell}$;
else
24 Increase $P_{t,n}^{RED}$;
25 t=t+1;
26 **if** *flag=1* **then**
27 Return to EMS unit;
28 $flag = 0$;

Later, the selling power of each MG is reduced proportional to its share, using (24), and the power flow is performed again to check if the issue was addressed. The initial guess for total reduction of the sold power of whole system is increased in each iteration, in case the problem was not solved. Those MGs who do not have any excess power to sell are eliminated from the allocation process as the algorithm runs iteratively.

$$P_{t,n}^{RED} = IG \times Share_{t,n} \qquad (where: \sum_n Share_{t,n} = 1). \quad (24)$$

Finally, the maximum amount of the power that each MG can sell without causing overvoltage and overcurrent to the system is obtained and it is given back to the first level as an additional constraint to repeat the optimization. Again, after the optimization, each MG sends its excess and shortage power data to the CEMS and CEMS performs power flow. This time, overvoltage may happen in different hours. Therefore, the process runs until a stable operating point is reached. The same process is repeated for the overcurrent problem when it happens.

It should be noted that this method only assigns the maximum allowable power selling limit to MGs for next day to ensure voltage and current regulation. The real-time transactions between MGs and the grid is studied in a third level which is out of the scope of this study. Moreover, since the MGs are grid-connected, the grid itself compensates for the immediate changes in the load and renewable power and regulates the frequency [37].

Overvoltage and overcurrent problems usually occur in the system due to aggregated DER generation such as simultaneous power generation of the rooftop photovoltaic systems or other similar phenomena that cause reverse power flow from distribution system to the transmission system for supplying other regions [38]. However, using this algorithm, MG operators can exploit the full potential of their DRs and DERs to sell maximum power and make maximum profit. Moreover, this structure enables avoiding power spillage in the network.

The second-level algorithm is a combination of allocation method and power flow and it converges because it only reduces the excess power of MGs until the network voltages are within the standard threshold. This algorithm will not converge only if the power flow does not converge. However, since the MGs in this study are connected to the grid, any shortage in power can be supplied by the main grid. Therefore, the mentioned condition will not occur in this model. Also, in general, many solutions exist for the second-level problem. However, the method presented by Algorithm II is unique due to being fair and ensures the optimum result for its specific purpose.

To sum up, the optimized variables in the first level of optimization are the charging and discharging power of the electrical storages, generated micro-turbine power, sold power to the grid, power bought from the grid, optimal thermostat setting, HVAC consumption and shifted load values. On the other hand, the optimized variables in the second level are the voltage profile of busbars, current flow of lines and the maximum power selling limit of each MG.

Proposing a bi-level model decreases the amount of data exchange between the individual houses and the central energy management system, it preserves customer privacy and it is less complex compared to other methods such as quadratic programming, dynamic programming etc., especially when the number of MGs in the system is high. Also, more MGs and customers can be easily added to the current model without a change in the formulation.

III. Results and Discussion

This section explains the tools, methods and data that were used for the simulation. The results and comparison to other studies is presented as well.

A. Simulation Data

The proposed model was validated over a standard 33 bus IEEE system, composed of five residential MGs operating in grid-connected mode. The structure is depicted in Fig. 3. The forward-backward method was utilized for the power flow process. The required house data, including individual loads, temperature, and wind data were obtained from Pecan Street Inc. [39]. Day-ahead electricity price was forecasted similar to [40].

For the training process (as previously mentioned in EMS unit), a two-layer neural network with 25 neurons together with back-propagation training method was used. The two-layer structure was chosen for this study to prevent overfitting and complexity in the model which may cause the EMS optimization to become infeasible as well. Based on the try and error approach, 25 neurons in the hidden layer ensures the minimum MSE for our model. Moreover, the back-propagation method was selected for training since it is fast and flexible about the structure of the neural network and it works well with the most of the structures.

Table I presents the number of generation resources and houses that each MG has. The technical data of the resources is given in Table II. Micro-turbine cost coefficients and wind turbine data were derived from [31] and [41], respectively. The programming environment for the deep learning process and

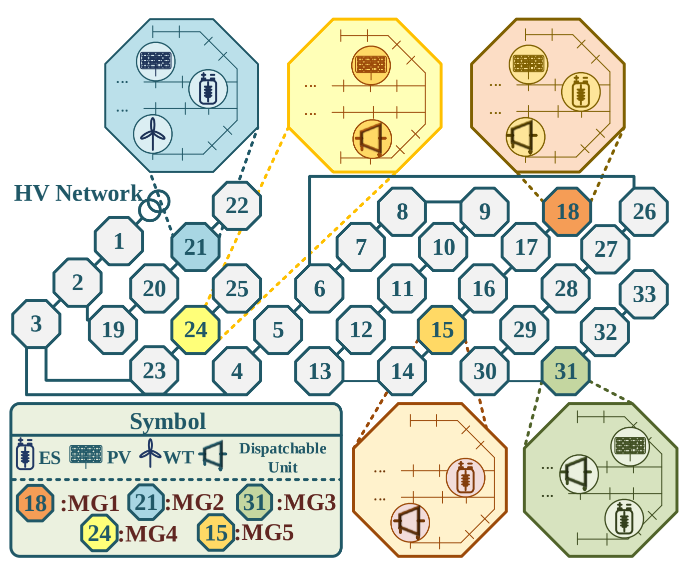


Fig. 3. Case study.

TABLE I
NUMBER OF LOCAL UNITS

Unit type	MT	PV	WT	Houses
MG#	Number of units			
MG1	1	1	0	6
MG2	0	1	1	5
MG3	1	1	0	5
MG4	0	1	0	3
MG5	0	1	0	2

TABLE II
PARAMETER VALUES

$Gen\#$	Type	$a^g[\$]$	$b^g[\$/kW]$	$c^g[\$/kW^2]$
1,3	MT	6	0.012	4.8×10^{-4}
$Gen\#$	$\overline{P}^{MT}[kW]$	$\underline{P}^{MT}[kW]$	SU [$]	SD [$]
1,3	250	50	4	0.5
$WT\#$	$\underline{v}\ [m/s]$	$\overline{v}\ [m/s]$	$v^r[m/s]$	$P^r[kW]$
2	4	22	10	50
$PV\#$	$A^{PV}[m^2]$	η^{PV}	$\overline{P}^{ES}[kW]$	η^{ch}, η^{dis}
1	20	0.2	250	0.85
2	15	0.2	70	0.9
3	15	0.2	250	0.85
4	10	0.2	3	0.9
5	8	0.2	2	0.9

CEMS management is MATLAB and the EMS optimization is modeled in General Algebraic Modeling System (GAMS). The simulation duration is 45 minutes using a 2.5 GHz Intel Core i5-4200 CPU with 6 GBs of random-access memory. Given that the proposed method runs day-ahead, 45 minutes is a useful time to provide solutions to the operators and end users.

B. Simulation Results

A comparison study for HVAC energy consumption was conducted as shown by Fig. 4, in which three scenarios were considered **Scenario 1**: with DR program and CEMS **Scenario 2**: with DR program and without CEMS, and **Scenario 3**: without DR program and CEMS.

As it can be observed, by performing DR, a significant amount of energy is saved. For the current case study, the total percentage of saved energy is 18.75%. In addition, as displayed by this figure, adding CEMS to the system almost has no effect on HVAC energy consumption.

Fig. 5 illustrates the amount of shiftable loads at each hour for the same three scenarios. By comparing these scenarios, it becomes evident that performing DR shifts only a part of the shiftable loads to low price hours, which is due to the presence of users' dissatisfaction. Most of the loads between the 14^{th} and 22^{th} hour are shifted to other times especially to 12^{th} and 13^{th} hour. Unlike the HVAC energy consumption, adding CEMS to the system has a lot of impact on changing shiftable loads pattern and it prevents creation of rebound peaks by preventing identical behavior of MGs.

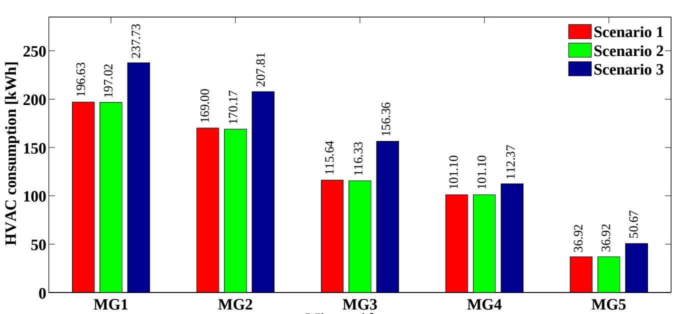
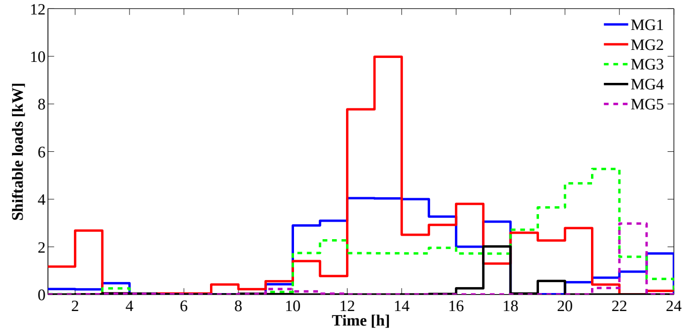
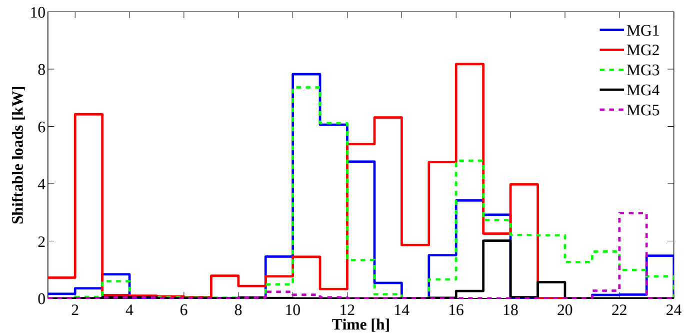


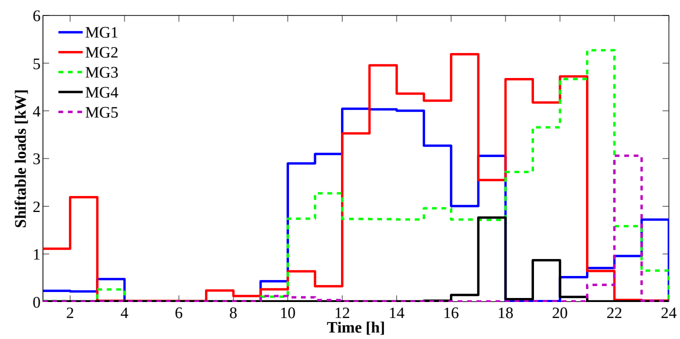
Fig. 4. Total HVAC energy consumption in one day.



(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

Fig. 5. Hourly shiftable load value inside each MG in three scenarios.

To prevent presenting a large amount of figures, only the individual HVAC consumption of the houses inside MG5 is depicted by Fig. 6. As it is visible from this figure, by performing training in scenarios 1 and 2, the HVAC consumption trend is maintained and depending on the overall comfort level and hourly comfort level of each house, energy usage is lessened. Therefore, current method was able to successfully model the user behavior regarding HVAC systems based on the history of user preferences in different hours.

The result of voltage correction, which is performed by CEMS, is displayed in Fig. 7. As can be seen, CEMS was successful in preventing the voltage deviation and making the voltage profile smoother. Furthermore, this structure gives MGs the chance to reschedule their resources and maximize their profit one day ahead compared to the time when they are forced to reduce production without previous notice for

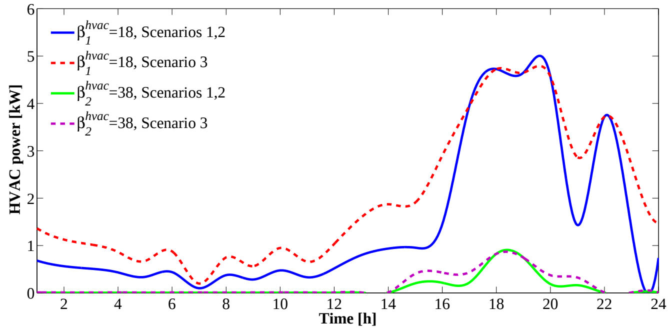


Fig. 6. Hourly HVAC energy consumption for houses inside MG5 in three scenarios.

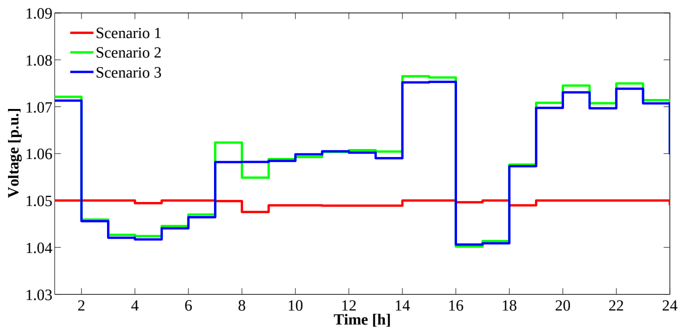


Fig. 7. Maximum voltage of the system in three scenarios.

voltage regulation.

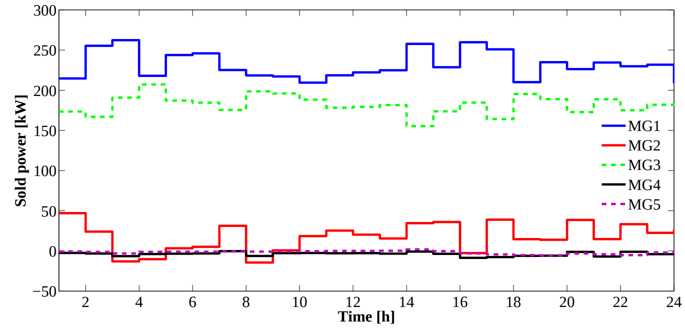
Fig. 8 represents the amount of sold power in the three scenarios. By adding CEMS to the system, MG1 and MG3 received maximum effect since they had maximum power production. On the other hand, MG4 and MG5 did not receive much impact, since they had very little or no sold power. The first two figures can be compared to understand the effect of CEMS in fairly limiting the MG power production to control voltage and current. For example, maximum overvoltage happens on the 33$^{\text{th}}$ busbar in this study and MG3 is the nearest MG to this busbar. Having the maximum impact on increasing the voltage of this busbar, it receives maximum power selling reduction.

The power generated by the renewable energy resources inside each MG is depicted in Fig. 9. MGs use all of the generated power by renewable units. They use a part of it to supply demands and to charge the storage and they sell the rest of it to the main grid.

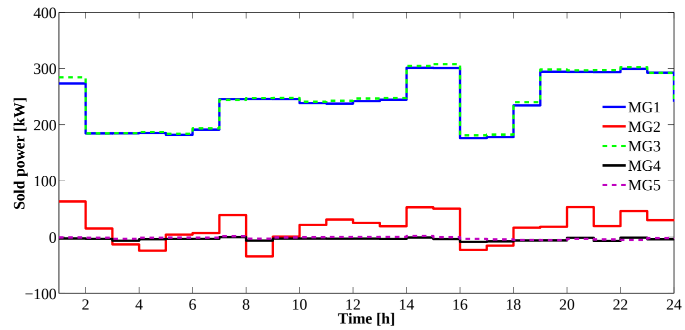
An overall comparison between the three scenarios is summarized in Table III. It can be concluded from this table that scenario 1 provides the best condition for our test system.

TABLE III
COMPARISON BETWEEN THE THREE SCENARIOS

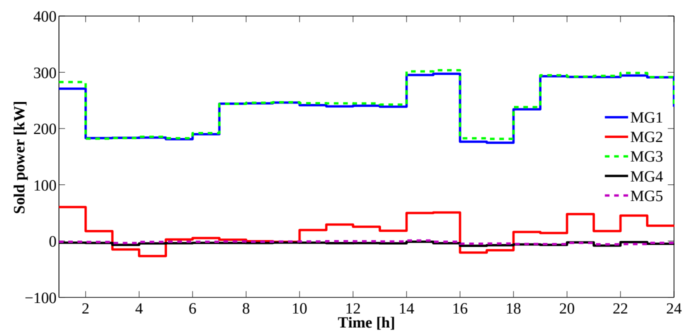
	Scenario 1	**Scenario 2**	**Scenario 3**
Average energy saved [kWh]	26.68	29.13	0
Average user dissatisfaction [$]	153.32	155.79	0
Average power selling limit [kW]	432.83	509.95	503.58
Total load peak [kW]	71.35	81.67	74.77
Voltage/current regulated?	Yes	No	No



(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

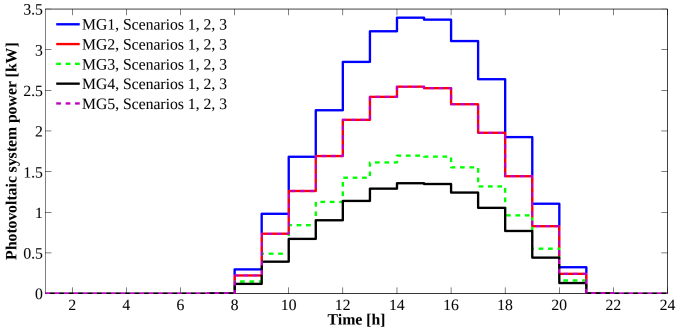
Fig. 8. Hourly sold power by each MG in three scenarios.

This is because in scenario 1, energy is saved, user satisfaction is fair, voltage and current limits are satisfied and load peak is the lowest. Although in this scenario MGs can sell less power, the fact is that in reality and in scenarios 2 and 3, MGs cannot sell as much power as the values indicated in Table III due to overvoltage or overcurrent issues that happen in the system.

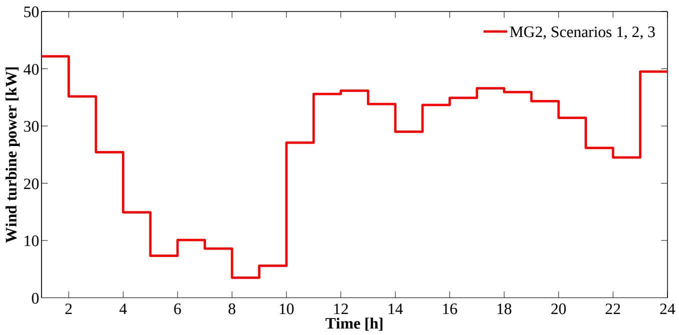
C. Comparative Study

The deep learning structure used in this study is compared to other possible structures and methods and the resultant MSEs are shown in Table IV. As can be seen, the neural network structure in this study, with 25 neurons in its hidden layer, has the lowest MSE among other structures and methods and for this reason, this structure was chosen for current study.

To illustrate the advantages of the proposed method in this paper, a comparison is made with the methods used for energy management of CoMGs in [12], [17], [18], [21], [22], [23] and the results are presented in Table V. It can be seen from this table that the fair-optimal method presented in this study can consider the voltage and current constraints of the system at



(a) Power generated by photovoltaic systems



(b) Power generated by wind turbines

Fig. 9. Power generated by renewable energy units in three scenarios.

TABLE IV
MEAN SQUARED ERROR OF DIFFERENT METHODS [KW^2]

Method	Average MSE	Min MSE	Max MSE
Proposed Method	0.3833	0.0008	1.7886
ANN with 10 neurons	0.5023	0.0027	2.2719
ANN with 15 neurons	0.4825	0.0016	2.0965
ANN with 20 neurons	0.4630	0.0017	2.0246
ANN with 30 neurons	0.4468	0.0014	1.9680
ANN with 35 neurons	0.4625	0.0014	2.0154
ANN with 40 neurons	0.4625	0.0015	2.0403
Linear regression	0.4639	0.0012	1.8393

the same time as reducing cost, preventing rebound peaks and modeling user behavior.

IV. Conclusion

A bi-level energy management structure was proposed in this study to overcome issues caused by aggregated DRs, DERs and user dissatisfaction due to DR programs while fulfilling power system constraints. Machine learning method was used in the first level to model user behavior and dissatisfaction regarding HVAC systems. Doing so, energy consumption of HVACs was reduced by 18.75% after optimization in a community of five MGs.

Introducing the power system limitations in the second level, changed the optimal operation points of MGs, which resulted in 12.64% decrease in the rebound peak created due to identical load shifting behavior of all MGs. Additionally, an allocation-based approach was proposed in the second level to fairly limit the power generation of MGs for voltage and current regulation while allowing maximum utilization of the DRs and DERs.

The principal benefits of the proposed bi-level structure can be summarized as follows: 1) finding best DR for each user based on his habitual behavior and minimizing dissatisfaction 2) using maximum capacity of the power system, DRs and DERs to increase individual MG profits without causing overvoltage, overcurrent and privacy issues in CoMGs 3) reducing load peak and rebound peak effect 4) flexibility of the current structure in adapting to changes in users' behavior and adding more MGs.

Future studies can focus on designing a model predictive control for online control of the proposed structure instead of the day-ahead control. To consider the influence of uncertainties, methods such as stochastic programming or weighted information gap decision theory (IGDT) can be used. Moreover, various bidding strategies can be added in a third level to study the behavior of MGs and their response to various price signals.

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TABLE V
COMPARISON OF THE PROPOSED ENERGY MANAGEMENT METHOD WITH OTHER STUDIES

Reference	Type of coordination	Objective function	Optimization algorithm	Test system	User behavior modeling	Power system constraints	Fairness considered?	Cost reduction	Peak reduction
Proposed method	Hierarchical	Cost,dissatisfaction voltage, current	MILP, algorithm 1	33 bus IEEE	Deep learning	Voltage, current	Yes	14.46%	12.64%
[17]	Centralized	Cost	Tabu search	PG&E 69 bus	None	Voltage, current	No	16%	×
[18]	Hierarchical	Cost & power mismatch	Artificial Bee Colony	37 bus IEEE	None	None	No	15.7%	×
[12]	Decentralized	Cost	Dynamic programming	Ohio State University ecosystem	Stochastic methods	None	No	-	12%
[21]	Hierarchical	Cost	Column & constraint generation	Taizhou, Zhejiang grid	None	Voltage	No	61.5%	×
[22]	Hierarchical	Cost, loss, dissatisfaction	Convex relaxation	Real 14 bus	None	Voltage	No	15.5%	×
[23]	Centralized	Cost, CO2	IPOPT solver	Savona campus 4 bus grid	None	Voltage	No	1.23%	×

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