Demand-Side Management by Regulating Charging and Discharging of the EV, ESS, and Utilizing Renewable Energy

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***Abstract*—The evolution in microgrid technologies as well as the integration of electric vehicles (EVs), energy storage systems (ESSs), and renewable energy sources will all play a significant role in balancing the planned generation of electricity and its real-time use. We propose a real-time decentralized demand-side management (RDCDSM) to adjust the real-time residential load to follow a preplanned day-ahead energy generation by the microgrid, based on predicted customers' aggregate load. A deviation from the predicted demand at the time of consumption is assumed to result in additional cost or penalty inflicted on the deviated customers. To develop our system, we formulate a game with mixed strategy which in the first phase (i.e., prediction phase) allows each customer to process the day ahead raw predicted demand to reduce the anticipated electricity cost by generating a flattened curve for its forecasted future demand. Then, in the second stage (i.e., allocation phase), customers play another game with mixed strategy to mitigate the deviation between the instantaneous real-time consumption and the day-ahead predicted one. To achieve this, customers exploit renewable energy and ESSs and decide optimal strategies for their charging/discharging, taking into account their operational constraints. RDCDSM will help the microgrid operator to better deal with uncertainties in the system through better planning its day-ahead electricity generation and purchase, thus increasing the quality of power delivery to the customer. We evaluate the performance of our method against a centralized allocation and an existing decentralized EV charge control noncooperative game method both of which rely on a day ahead demand prediction without any refinement. We run simulations with various microgrid configurations, by varying the load and generated power, and compare the outcomes.**

***Index Terms*—Demand-side management (DSM), demand forecasting, electric vehicles (EVs), energy storage, game theory, home energy management system (HEMS), mixed strategy, microgrids, optimization, renewable energy sources (RESs), smart grids.**

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I. Introduction

The rapid surge in demand for electricity is considered as one of the most significant problems that is faced by the power grid. To achieve higher reliability, robustness, and stability, today's power grids are designed to serve peak demands rather than the average load. This can result in a power generation and distribution system that is underutilized as well as in the waste of natural resources [1], [2]. Hence, utility companies are continuously adjusting the power generation of their plants to balance the total loads and their variations. Indeed, fast-responding generators such as fossil-fuel generators are costly and have a significant greenhouse gas footprint [3]. Power system planners are, therefore, facing a pressing challenge to meet their customers surging demands while ensuring electricity systems integrity. Numerous methods have been proposed to alleviate problems of uncertainties in power system and regulate users' consumption profiles. The aim of these plans (such as demand-side management or DSM) is to deploy the current capacity more efficiently without modifying the existing grid infrastructure [2], [4]–[7]. The evolution of the smart grid, integration of renewable energy source (RES), advanced metering infrastructure smart meters, electric vehicles (EVs), and dynamic pricing have all added momentum to solve the DSM problem efficiently. Furthermore, the widespread deployment of home energy management systems (HEMS) and communicating devices will upgrade the existing power grid structure and transform it into a more intelligent and decentralized system [8].

Recently, new distributed entities that have not existed previously, e.g., microgrids and active distribution networks, are becoming essential components of the smart grid. A microgrid is a miniature form of the smart grid which enables a two-way communication to exchange control and information between customers and the operator. The integration of RESs, energy storage systems (ESSs), and EVs as key components in the microgrid can lead to imbalances in the system (e.g., due to the stochastic nature of RES, randomness arising from EV's behavior, etc.) and further aggravates the problem of load uncertainties. ESSs and EVs can, however, also present new opportunities for the DSM and can be employed to store energy when demand is low compared to the amount of production from RESs and discharge it in times of shortage or peak demands [9]. Now, the amount of renewable energy, electricity demand for residential use, charging and discharging of EVs, all vary at the time of operation compared to the day-ahead prediction [9]–[11]. Typically, the energy must be either consumed or stored at its precise production moment, whereas the demand for it varies throughout the day and across the seasons [9], [10]. As a result, the utility–customer interactions vary depending on the timescales as well as the types of customers units [12]. Most efficient forecast methods do not accurately predict the RES generation, household, and EV demands; therefore, a discrepancy exists between the predicted load and the actual use of electricity by the customers of the grid[13]. Moreover, the variation between predicted and actual load is primarily dependent on the forecast methods and quality. This can be reduced by encouraging customers to use better prediction methods or change their consumption behavior (e.g., stick to the predicted consumption). In addition to this, smart meters enable automated collection of fine grain consumption readings and dynamic pricing which depends on the time-of-day in order to reduce energy demand. Smart meter load profiling by exploiting large volume of historical data will provide a new avenue of opportunity to learn the consumption and production pattern of the customers and power grid [14]. Much work has been done for determining customer load using the smart meter which is certainly a useful source for estimating a variety of customer loads [15]–[17].

More recently, much research work has been done to address the DSM problem. In [5], the authors presented a heuristic-based evolutionary algorithm to solve the DSM based on a day-ahead load shifting technique for a microgrid which contains a large number of devices. Their results show that the proposed strategy achieves substantial savings while reducing the peak load. In [6], the authors studied the reverse power flow problem from rooftop photovoltaic (PV) elements to the substation which causes a rise in voltage when generation is larger than the aggregated load. The authors proposed a DSM system that shifts the operation of deferrable loads from peak consumption hours to high PV production periods. The simulation results showed that the proposed methods solve the voltage rise problem in an area with penetration of PVs. In [7], the authors studied a real-time-based DSM with advanced communication networks and proposed a game theoretic solution to smooth the peak-to-average ratio. In [18], a new approach to forecasting the residential electricity demand over 24 h is presented; each consumer is responsible for predicting his future loads and sharing that outlook with the operator. For DSM, the authors discuss a reward which will be given to the customers based on the accuracy of their forecasts. Caron and Kesidis [8] introduced a dynamic pricing scheme to motivate the customers to come up with an aggregate load profile suitable for the utility. In [19], Rossi and Brunelli assessed the performance of exponential smoothing forecasting techniques in forecasting the energy demands of residential users. A real-time game theoretic distributed algorithm is proposed to minimize customer bills by reducing peak demand [9]. RESs and EVs are used to transfer energy from one duration to another duration and schedule equipment to reduce the peak-demand and flatten the load curve [9].

The remainder of the paper is organized as follows. Section II describes the proposed model and highlights some significant contribution of this research work. In Section III, we describe the mathematical model for household load, RES, EV, and ESS. In Section IV, we present the problem formulation and game theoretical solution [real-time decentralized demand-side management (RDCDSM)]. We analyze and describe the results of the simulation in Section V. Finally, we conclude in Section VI.

II. Problem Statement and Contribution

We consider a residential microgrid which is connected to the grid and purchases electricity from it according to its customers aggregated day-ahead predicted demand. Each client predicts its load a day-ahead and sends it to the operator. Upon receiving this information, the microgrid operator plans to purchase electricity for the next day (to satisfy its users' demands) and determine the energy cost accordingly. At the time of operation, however, the actual user's demand may change, and the renewable power generation may vary, which results in discrepancy and instability in power delivery and thus increases the cost. The user consumption behavior, the quality of the prediction method, and electricity usage by the user may further aggravate the deviation.

To solve this problem, we propose an RDCDSM which in the first place encourages customers collectively to modify their day-ahead coarse anticipated consumption to minimize their electricity cost, or inversely increase their payoff to produce a fine-grain predicted demand. Customers will play mixed strategy in a noncooperative game by sharing their day-ahead anticipated demand and continuously modify it to increase their payoff. The game terminates in a Nash equilibrium state, which results in a fine-grain price-aware predicted demand where a further change of demand will not increase the payoff. Then, each customer sends its resultant predicted demand to the operator. Upon receiving and accumulating the anticipated demand from its customers, the operator produces the day ahead aggregate predicted demand and devises a plan to generate and purchase electricity according to the projected requirement for the next day, to satisfy the needs of the customers. We define this as the prediction phase of RDCDSM.

Next, in step two, known as the allocation phase, the RDCDSM system encourages customers, in real time, to adjust their consumption pattern to stay close to their predicted demand. Doing so will allow the microgrid to stick to its predetermined energy generation/purchase plan and avoid the higher costs of either activating a new generator or buying electricity at the instantaneous market price. To achieve this objective, customers in each time slot adjust their forecast of future demands and RES energy generation and determine operation strategies for charging and discharging of EVs, microgrid ESS (MESS), and ESSs to mitigate the deviation between the current real-time load and their originally predicted (price-aware) load. All customers play another game with mixed strategy to reduce the penalty or increase the payoff. The interplay terminates at a Nash equilibrium state similar to the prediction phase.

The customers will play the game in each time slot as long as a change in demand concerning fine grain predicted load is detected for the current and future time slots. Finally, the system will penalize (i.e., higher rate charge) each of deviated users with the proportion of the total deviation determined by the operator.

In RDCDSM, each customer is encouraged to trade electricity with other and the central ESS to reduce the gap between the predicted and actual consumption. In our microgrid system, we assume that some homes have rooftop solar panels (RES) each with a small, inexpensive ESS and EV. The microgrid is also expected to have a large centralized ESS (MESS) to store extra power generated by the RES, and it is used (discharged) when there is a shortage. Each EV is capable of vehicle to grid (V2G) which charges to a target amount of energy before going to next drive.

We use a short-term forecasting of the electricity demand over 24 h, seven days, which is better known as *short-term load forecasting* (STLF) [20]. We study how smartly using those methods can constitute a significant advantage for the consumers interested in reducing their energy usage. RESs, MESS, ESSs, and EVs allow the user not only to mitigate the deviation between forecast and actual loads but also reduce its dependence on the utility. Hence, adding to the benefits mentioned earlier, our approach assures overall social and environmental benefits for the community. MESS, ESSs, and EVs play a vital role in balancing the supply and demand. We start by synthesizing and process the expected electricity request for household users over a 24-h period to minimize the generation cost. Then, we apply our proposed model to show, how the gaps between the resulting aggregated forecast and the real demand are reduced. The advantage of reducing these gaps helps the user to abide by his predictions and provide the producer with the more precise production schedule. In that event, the user maximizes his monetary gains, and conversely, the retailers reduce their total variable cost without harming the integrity of the power grid.

The main contribution of this paper is then to design a novel cooperative strategy (RDCDSM) between the residential consumers and their energy suppliers. In this cooperation, the operator asks each household to submit and adhere to its fine-grain forecast of electricity usage a day-ahead. We formulate a two-stage game theoretical model that minimizes the energy cost, and the difference between the households aggregated predicted and real demands. We show that by using our model, each customer can autonomously cooperate with other consumers and enhance his/her ability to adjust his/her need.

III. System Model

We consider a grid-connected residential microgrid (shown in Fig. 1) which comprises a set of customers $\mathcal{N}$. Each of the customers may be equipped with an RES with an ESS and an EV (with V2G capabilities). We assume each home is connected to an HEMS which connects it to the microgrid operator as well as with other consumers. Each day, the HEMS of each user forecasts the load, energy generation from RES, and (if applicable) the EV target energy and its driving schedule, thus determining a probable consumption profile for the next 24 h. The predicted demand of a customer n in time slot t is calculated as

$$p_n^t = l_{n,p}^t + \alpha_{n,p}^t + \theta_{n,p}^t + \epsilon_{n,p}^t - w_{n,p}^t \quad \forall t \tag{1}$$

where p_n^t, $\alpha_{n,p}^t$, $\epsilon_{n,p}^t$, $\theta_{n,p}^t \in \mathbb{R}$ define the probable consumption profile, customer ESS, centralized ESS, and EV's energy level for the customer n. The predicted load and the amount

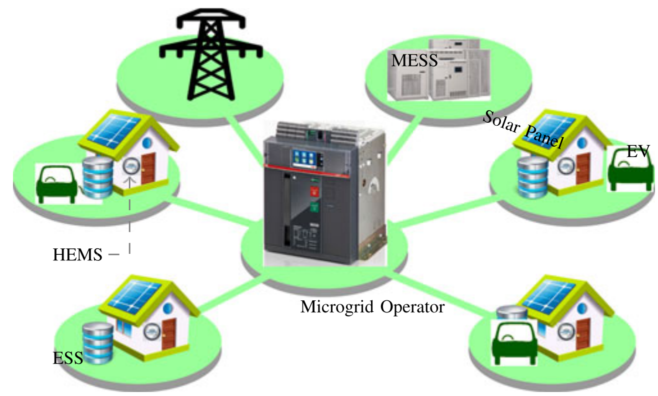

Fig. 1. Residential smart microgrid.

of energy used from RES are $l_{n,p}^t$ and $w_{n,p}^t$, respectively, and $l_{n,p}^t, w_{n,p}^t \in \mathbb{R}^+$. Each customer optimizes its predicted load and communicates its fine-grain predicted demand (p_n^t) for next 24 h with the microgrid operator. The microgrid operator is responsible for planning and controlling the flow of electricity among users in the network. Let $\mathcal{G}(t)$ be the amount of electricity purchased from the main grid at time t to support the fine-grain projected demands of $\mathcal{N}$ at t. At consumption time, customer compares its real demand with the proposed predicted demand p_n^t. Any discrepancy triggers the customers to play an allocation game between them to minimize the gap between the predicted and actual needs (and thus avoiding higher penalties). For all t, our proposed system allocates electricity from the microgrid to every home based on the home's actual consumption.

To formulate a mathematical model for RDCDSM, we investigate the prediction of residential loads, RES energy generation, ESS features, as well as the EVs' driving schedules and distances. For simplicity, we illustrate the consumption pattern of each of the components of the residential home. We present the mathematical model of each of the elements before formulating the RDCDSM problem.

A. Residential Load ($l_{n,p}^t$)

Most useful load forecast models are based on offline schemes, where predictions are conducted in advance. The uncertainty of prediction increases with the growth of the forecast time [9]. The STLF is, thus, more accurate than mid-term load forecast or long-term load forecast [9]. Currently, several STLF techniques exist, but aside from their varieties, these methods mainly depend on historical demands, weather forecasts, and other variables to estimate the aggregated demand of all consumers [10]. However, the efficiency of any prediction depends not only on the accuracy and time horizon of the forecast but also on its capability to reduce the complexity, cost, and memory needed for predicting the customer demand [10], [19]. In the proposed system, we suppose that each residence is connected to an HEMS. These HEMSs are enabled to assist consumers in forecasting their load based on an average household demand [20], and refine and send the data over a data network to other customers and the operator [10]. Moreover, the HEMSs provide a real-time two-way interaction with the microgrid operator and other clients. A consumer first sends its fie-grain predictions for the next 24 h at the start of the day. Next, at each time slot, a user determines its consumption strategy for its actual demand in the current slot and modifes its forecast demand for the rest of the day. This forecasting approach reduces the complexity of real-time electricity demand by shifting the forecast burden from the operator to the customers, enhancing the accuracy of the predictions. Now, let the predicted load of n be $l^t_{n,p}$ and the predicted load of the microgrid be δ^t_p at t, then

$$\delta^t_p = \sum_{n\in\mathcal{N}} l^t_{n,p} \quad \forall t. \tag{2}$$

B. Renewable Energy ($\omega^t_{n,p}$)

We assume that RESs are available for some homes. RESs such as solar PV and wind turbines generate electricity in random [21]. However, the RES provides a great promise for significantly improving the efficiency of distribution, and residential renewable energy generation is becoming more popular as the installation cost is decreasing and prices are rising [12], [21]. Hence, several stochastic models have been developed to forecast the energy generation over time, and thereby, to enhance RESs exploitation and penetration in smart grids. In our proposed system, the customer decides whether to store the energy generated by the RES or to supply it to other clients, according to the power demands in every real-time slot (t_s). Let $\omega^t_{n,p}$ be the predicted amount of electricity used from RES where $\Omega^t_{n,p}$ denotes the predicted generation and entire predicted generation at t be ω^t_p. Then

$$\omega^t_{n,p} \le \Omega^t_{n,p};\ \omega^t_p = \sum_{n\in\mathcal{N}} \omega^t_{n,p} \quad \forall t. \tag{3}$$

C. Energy Storage System—ESS ($\alpha^t_{n,p}$)

The introduction of new types of batteries with higher storage capacities has encouraged ESS to emerge as a way to improve the power management in smart grid [22], [23]. ESSs play a vital role in matching the generation with demand which leads to an increase in the efficiency and reliability of the system against uncertainties. In general, every home with an RES has an ESS installed to store the excess energy which is used later when the demand is high. Now, let the charging and discharging strategies of an ESS b of n at time t be $\alpha^t_{n,b} \in \{-X^{\text{low}}_{n,b}, \ldots, 0, \ldots, X^{\text{high}}_{n,b}\}$, where $-X^{\text{low}}_{n,b}$ denotes extreme discharge rate and $X^{\text{high}}_{n,b}$ denotes the maximum charging rate. Let the amount of charging and discharging of ESS of n at time t be $c^t_{n,b}$ and $d^t_{n,b}$, then $\forall t$ we have

$$0 \le c^t_{n,b} \le (X^{\text{high}}_{n,b} \cdot \eta^t_{n,b});\ 0 \le d^t_{n,b} \le (X^{\text{low}}_{n,b} \cdot (1-\eta^t_{n,b})) \tag{4}$$

where $\eta^t_{n,b}$ is a binary variable; $\eta^t_{n,b} = 1$ indicates that ESS b is charging at time t; otherwise, it is discharging. Let $\Phi^c_{n,b}$, $\Phi^d_{n,b}$ be the charging and discharging efficiency of b, then

$$\alpha^t_{n,b} = \frac{c^t_{n,b}}{\Phi^c_{n,b}} - d^t_{n,b} \cdot \Phi^d_{n,b}. \tag{5}$$

Note that ESSs have a maximum capacity and minimum discharge level. For both safety and longevity, this should always be maintained. Thus, for any time slot t, ESS b must not discharge below its minimum discharge level $\mathcal{C}^{\min}_{n,b}$, and charge over the capacity $\mathcal{C}^{\max}_{n,b}$. Thus

$$\mathcal{C}^{\max}_{n,b} \ge \mathcal{C}^{\text{init}}_{n,b} + \sum_{t=t_s}^{T} (c^t_{n,b} - d^t_{n,b}) \ge \mathcal{C}^{\min}_{n,b} \tag{6}$$

where $\mathcal{C}^{\text{init}}_{n,b}$ is the initial energy stored in the ESS at the start of the day. Now, let the probable strategy of battery b at time t be $\alpha^t_{n,p}$, then $\alpha^t_{n,p} = \alpha^t_{n,b}$. We assume that each residential customer has an ESS which is connected to the RES.

D. Electric Vehicle ($\theta^t_{n,p}$)

Large-scale energy storage requires vast land spaces, high installation, operation, and maintenance costs [9], [24]. Conversely, compared with oversized storage devices, plug-in EVs can be used as a cheap way to store and transport the surplus of energy. EVs may appear as loads during charging periods; meanwhile, they may also be used as storage to store the surplus of energy or discharge stored energy to balance the demand and generation in the smart grid [24]. Hence, EV may charge, discharge, or remain idle throughout the day. According to [25], we assume that the EVs arrive home in the evening with an arbitrary initial energy level. An EV stays connected to the home for a random amount of time and then leaves home in the morning for the next driving. When connected to the microgrid, the energy stored in a given EV must attain a certain target level required for the following driving schedule. Let the arrival and departure time of a given EV e of consumer n be $t^a_{n,e}$ and $t^d_{n,e}$, respectively. Also, let $\mathcal{T}_{n,e}$ be the set of time slots during which an EV e of n is connected to the grid, where $\mathcal{T}_{n,e} \triangleq \{t^a_{n,e}, t^a_e + \Delta t, t^a_e + 2 * \Delta t, ..., t^d_{n,e}\}$. Now, suppose the charging and discharging rate of the EV be $\theta^t_{n,e} \in \{-Y^{\text{low}}_{n,e}, \ldots, 0, \ldots, Y^{\text{high}}_{n,e}\}$, where $-Y^{\text{low}}_{n,e}$ denotes extreme discharge rate and $Y^{\text{high}}_{n,e}$ denotes the maximum charging rate. For EVs, similar to the ESSs, (4)–(6) must be satisfied only for timeslots $t \in \mathcal{T}_{n,e}$. Let the amount of charging and discharging of an EV e of consumer n at time t be $r^t_{n,e}$ and $v^t_{n,e}$ accordingly, then

$$0 \le r^t_{n,e} \le (Y^{\text{high}}_{n,e} \cdot \zeta^t_{n,e});\ 0 \le v^t_{n,e} \le (Y^{\text{low},e}_{n,e} \cdot (1-\zeta^t_{n,e})) \tag{7}$$

$$\theta^t_{n,e} = \frac{r^t_{n,e}}{\Phi^r_{n,e}} - v^t_{n,e} \cdot \Phi^v_{n,e} \tag{8}$$

where $\zeta^t_{n,e}$ is a binary variable and $\zeta^t_{n,e} = 1$ indicates EV charging at time t, otherwise discharging, and $\Phi^r_{n,e}$, $\Phi^v_{n,e}$ denote the charging and discharging efficiency of EV. Similar to ESS [see (6)], for any time slot t, EVs' strategy must satisfy

$$\mathcal{R}^{\max}_{n,e} \ge \mathcal{R}^{\text{init}}_{n,e} + \sum_{t=t^a_{n,e}}^{t^d_{n,e}} (r^t_{n,e} - v^t_{n,e}) \ge \mathcal{R}^{\min}_{n,e},$$
$$\forall t \in \mathcal{T}_{n,e},\ \forall e \in \mathcal{V} \tag{9}$$

where $\mathcal{R}^{\text{init}}_{n,e}$, $\mathcal{R}^{\max}_{n,e}$, and $\mathcal{R}^{\min}_{n,e}$ are the initial, minimum discharge, and maximum capacity of the EV. Moreover, before leaving the home for the next driving schedule, the energy stored in a given EV must attain a certain target level $\mathcal{L}_{n,e}$ (in kWh). Then, for an EV, the following equation must hold:

$$\mathcal{R}_{n,e}^{\text{init}} + \sum_{t \in \mathcal{T}_{n,e}} (r_{n,e}^t - v_{n,e}^t) \geq \mathcal{L}_{n,e}. \quad (10)$$

In general, an EV consumes 0.13–0.20 kWh/km [25] and the average daily trip length of 90% of EVs is between 20 and 60 km [26]–[28]. Most customers also use their vehicles from 6 : 00 am to 10 : 00 A.M. to drive to work and return home after work from 4 : 00 to 8 : 00 P.M. Let $\tau_{n,e}$ be the trip length of an EV and the amount of energy stored in an EV (before the trip) be $\mathcal{L}_{n,e}$, then the initial energy stored in an EV (when arrived at home) can be calculated as

$$\mathcal{R}_{n,e}^{\text{init}} = \mathcal{L}_{n,e} - \tau_{n,e} * \rho_{n,e} \quad (11)$$

where $\rho_{n,e}$ is an amount (kWh) of electricity consumed by the EV to drive 1 km. Now, let us assume that a customer has an EV. Then, the probable EV consumption profile $\theta_{n,p}^t$ at t can be assigned as $\theta_{n,p}^t = \theta_{n,e}^t$.

IV. Problem Formulation

We assume the microgrid operator plans its energy production and/or purchase a day ahead, based on the aggregate predicted demand it received from its users. However, the actual user's consumption and need for energy during the day may vary from its predicted demand. The frequent changes in demand may force the microgrid to produce a variable amount of power which either may not be possible, or expensive, on a short notice. Moreover, the start or shut down of a generator to match the user's variable demands involves substantial cost and time. Thus, our system will help the microgrid operator as well as the users to close the gap between the real-time and instantaneous actual and predicted aggregate demands. The integration of ESS, EVs, and an intelligent energy management system will be exploited to help in mitigating the problem and thereby reducing the electricity costs and instability in power generation.

We address these issues and design an intelligent solution (i.e., RDCDSM) to reduce the electricity costs by first flattening the predicted demand (or load curve) at the start of a day. The system then delivers electricity to the customers according to their actual demands, such that the deviation between actual and predicted demands is minimized. The RDCDSM has two consecutive phases: 1) prediction or planning phase and 2) allocation phase.

A. Prediction Phase

Each day, each home predicts its load, forecasts its renewable energy generation, EV arrival and departure times, and target energy. Next, all customers individually optimize, and flatten, their anticipated consumption pattern to reduce the cost, and then sends the resultant predicted load to the operator. To devise a fine-grain price-driven predicted consumption profile, each customer plays mixed strategy with others to determine the consumption strategy which is expressed by the variables, $\alpha_{n,p}^t$, $\epsilon_{n,p}^t$, $\theta_{n,p}^t$, $\omega_{n,p}^t \forall t \in T$, where $\epsilon_{n,p}^t$ is the optimal charging or discharging strategy of the MESS. Let γ_n^t be the feasible strategy of n such that $\gamma_n^t = \{\alpha_{n,p}^t, \epsilon_{n,p}^t, \theta_{n,p}^t, \omega_{n,p}^t\}$. Now, let γ_{-n}^t be the strategy of all other customers which results in a consumption p_{-n}^t at t given by

$$p_{-n}^t = \sum_{m \in \mathcal{N} \backslash n} (l_{m,p}^t + \alpha_{m,p}^t + \epsilon_{m,p}^t + \theta_{m,p}^t - \omega_{m,p}^t) \quad \forall t \in T \quad (12)$$

and consumption p_n^t of customer n is calculated as

$$p_n^t = (l_{n,p}^t + \alpha_{n,p}^t + \epsilon_{n,p}^t + \theta_{n,p}^t - \omega_{n,p}^t) \quad \forall t \in T \quad (13)$$

where $(p_n^t + p_{-n}^t) \geq 0 \; \forall t$. Let γ_{-n}^t or p_{-n}^t be known to customer n which is the current load of all other customers due to their current consumption strategies. A customer sends its load profile to other clients each time when the change of its previous strategy is *profitable*. Upon receiving the load profiles from other clients, customer n determines its next strategy $\gamma_n^t \; \forall t$ to increase the payoff which is given by

$$\sigma_n(\gamma_n^t, \gamma_{-n}^t) = Z - \min \left[\sum_{t \in T} (aP_t^2 + bP_t + c) \right] \quad (14)$$

where Z is a positive constant, a, b, and c are positive coefficients and $a >= b$. $aP_t^2 + bP_t + c$ is a quadratic cost function for electricity [29]. The variable P_t is the total amount of electricity which will be (or projected to be) consumed at t and it is defined as

$$P_t = p_n^t + p_{-n}^t \quad \forall t \in T. \quad (15)$$

$P_t \geq 0$, thus the cost function $aP_t^2 + bP_t + c$ is convex and the price-driven strategies in γ_n^t are all continuous and therefore the game will converge to a Nash equilibrium state and give an optimal solution. At a Nash equilibrium state (see Lemma 1), let the strategy of any customer n be γ_n^{t*}, then for any other strategies γ_n^t, $\sigma_n(\gamma_n^{t*}, \gamma_{-n}^{t*}) \geq \sigma_n(\gamma_n^t, \gamma_{-n}^{t*})$.

Lemma 1 (Nash Equilibrium): Energy planning noncooperative game in the prediction phase for $\mathcal{N}$ residential customers (players) has at least a Nash equilibrium.

Proof: According to the Nash's theorem, every noncooperation game with a finite number of players and action profile has at least one mixed strategy Nash equilibrium [30]. The energy planning game is a noncooperative game, and each of the players (residential home) plays a mixed strategy to charge, discharge EV and ESS. For charging ESS, residential players will pick any probable value between 0 and 1 (Pr), that is multiplied by a maximum charging rate $X_{n,b}^{\text{high}}$, i.e., $c_{n,b}^t = \text{Pr} \times X_{n,b}^{\text{high}}$ to increase its own payoff, i.e., (12). Alternatively, we can write $\text{Pr} \times X_{n,b}^{\text{high}}$ as $0 \leq c_{n,b}^t \leq X_{n,b}^{\text{high}}$. Likewise, it can be shown that all the strategies played by the players (residential customers) are mixed strategies. Thus, the energy planning game has at least one mixed strategy Nash equilibrium. ■

Once done, then all customers send their fine-grain predicted demand $p_n^{*t} \quad \forall t$ (for the strategy γ_n^{t*}) to the operator. Upon receiving the predicted demand, the operator sets a plan to produce or purchase electricity from the grid. Hence, the day-ahead price-driven predicted load ($P_{\mathcal{N}}^t \quad \forall t$) determined by the operator is

$$P_{\mathcal{N}}^t = \sum_{n \in \mathcal{N}} p_n^t \quad \forall t \in T. \quad (16)$$

B. Allocation Phase

Unfortunately, the uncertainties in household demands, RES generation, arrival and departure times of EVs, and their target energy may vary at the time of consumption from the predicted one. Hence, each customer needs to adjust its electricity usage at time of consumption to mitigate the gap between the actual and the predicted demand. Otherwise, the microgrid will respond by purchasing the extra energy needed (to satisfy the demands) and hence charges an extra cost (or penalty) proportional to the deviation between the actual and predicted demand of electricity.

Let us assume that the current time slot is t_s. Each customer reforecasts its demand (i.e., modified demand) for the period from t_s to $|T|$. Since there may be some gap between the actual (at t_s) and the predicted demand for this time slot, the customer will try to mitigate this difference by exploiting MESS, ESS, and EV as well as the customer's new forecast of RES, taking into account the constraints imposed by EV's departure times as well as target energy. A strategy is decided where to discharge energy from or where to store the excess of energy.

Hence, each customer plays a new game with mixed strategy, at t_s, with the current need and the modified (adjusted) predicted demand for rest of the day ($\forall t > t_s$). Therefore, the objective of the play is to reduce the penalty for the deviation of present and anticipated future needs from that of the submitted consumption pattern. Let Q be a fixed amount of additional cost (penalty) charged for one unit of electricity due to the deviation from the price-aware predicted demand. Then, the payoff for customer (n) can be calculated as

$$\bar{\sigma}_n(\gamma_n^{t_s}, \gamma_{-n}^{t_s}) = Z - \min \sum_{t=t_s}^{T} Q|P_{\mathcal{N}}^t - \bar{p}_n^t - \bar{p}_{-n}^t| \tag{17}$$

where $\bar{p}_n^t$ is the current (t_s) and future demands based on the current and projected household demands $\bar{l}_{n,p}^t$, EVs' consumption (charging and discharging) $\bar{\theta}_n^t$ with respect to new arrival and/or departure times and target energy, ESS consumption $\bar{\alpha}_n^t$, current and modified predicted generation of RES $\bar{w}_n^t$, and new charging and discharging strategies of the MESS $P_{\mathcal{N}}^t$. The absolute part of the payoff [see (17)] can be simplified as

$$\bar{\sigma}_n(\gamma_n^{t_s}, \gamma_{-n}^{t_s}) = Z - \min \sum_{t=t_s}^{T} Q y^t \tag{18}$$

such that

$$y^t \geq (P_{\mathcal{N}}^t - \bar{p}_n^t - \bar{p}_{-n}^t) \text{ and } y^t \geq (\bar{p}_n^t + \bar{p}_{-n}^t - P_{\mathcal{N}}^t) \tag{19}$$

where $\bar{p}_n^t$ for strategy $\gamma_n^{t_s}(\bar{\theta}_n^t, \bar{\alpha}_n^t, \bar{\epsilon}_{n,p}^t, \bar{w}_n^t)$ at time t_s can be determined as

$$\bar{p}_n^t = \bar{l}_n^t + \bar{\alpha}_n^t + \bar{\epsilon}_{n,p}^t - \bar{w}_n^t \quad \forall t \tag{20}$$

where $t_s \leq t \leq |T|$, and $\bar{p}_{-n}^t$ is

$$\bar{p}_{-n}^t = \bar{l}_{-n}^t + \bar{\alpha}_{-n}^t + \bar{\epsilon}_{n,p}^t - \bar{w}_{-n}^t \quad \forall t. \tag{21}$$

Similar to the game in the earlier Section IV-A and Lemma 1, it can be shown that the allocation game terminates at a Nash equilibrium state where no consumer is willing to change its strategy which results in reducing the payoff.

C. Centralized Allocation Model With Original Prediction

In the centralized method, the microgrid operator makes decision on behalf of its customers. Namely, in each time slot (t_s), each customer will send its actual load (for this time slot) as well as the reforecast of the projected demand ($\forall t > t_s$) and its modified prediction of the energy generated from renewable sources. Now, similar to the distributed method, the operator will attempt to mitigate the difference between actual and original predicted load (for t_s), by exploiting the energy storage systems (MESS, ESS, and EVs) taking into account the constraints (e.g., for EVs' departure times and target energy) transferred by the users. The centralized method does not shift loads to flatten the load curve and hence does not lower electricity price. The centralized allocation model can be realized by considering strategies $l_{n,p}^t$, $\alpha_{n,p}^t$, $\epsilon_{n,p}^t$, $\theta_{n,p}^t$, $\omega_{n,p}^t$ of n at t. Let load at t of n be $\tilde{p}_n^t$, then $\tilde{p}_n^t = (l_{n,p}^t + \alpha_{n,p}^t + \epsilon_{n,p}^t + \theta_{n,p}^t - \omega_{m,p}^t)$ For each time slot, the allocation of the electricity for each home can be determined, by the operator, by solving the following (22) with the related constraints. Hence, the objective function for the centralized model is

$$\min \sum_{t=t_s}^{|T|} Q\tilde{y} \quad \forall t_s \in T. \tag{22}$$

Such that

$$\tilde{y} \geq \tilde{P}_{\mathcal{N}}^t - \sum_{n \in \mathcal{N}} \tilde{p}_n^t;\ \tilde{y} \geq \sum_{n \in \mathcal{N}} \tilde{p}_n^t - \tilde{P}_{\mathcal{N}}^t \tag{23}$$

where $\tilde{P}_{\mathcal{N}}^t$ is the originally predicted load, which is determined by the microgrid at the beginning of the day by accumulating raw predicted load sent by the customers (original prediction). Here, $\tilde{P}_{\mathcal{N}}^t = \sum_{n \in \mathcal{N}} (l_{n,p}^t + \theta_{n,p}^t - \omega_{n,p}^t)$ such that $\tilde{P}_{\mathcal{N}}^t \geq 0$, which keeps a balance between energy production and consumption. $\theta_{n,p}^t$ designates the charging strategy of EV; here, as soon as an EV arrives, it starts charging at full charging capacity until a target ($\mathcal{L}_{n,e}$) is achieved. $\tilde{p}_n^t$ is the load which contains the current (i.e., in time slot t_s) and modified future demand of customer n. The objective can be linearize similar to (17).

V. Numerical Evaluation

A. Simulation Setup

We consider grid-connected microgrids with 100, 200, 300, ..., 1000 homes connected to each other through an electrical and a data network. Each customer has an energy management system (HEMS) which is responsible for forecasting the load, RES generation, EV arrival and departure times, and target energy level, and for sending (and receiving) information about energy, load, and other control information to other HEMSs. Each HEMS runs the energy optimization (RDCDSM) model to optimize the energy usage of the owner. A data network carries load and control information from one HEMS to other HEMSs as well as to the operator. The HEMS forecasts the household load for a day based on the average residential hourly load which given in [9] and [20]. For our simulations, we assume that each household consumes around 4 to 20 kWh per day. We consider RESs with capacities between 0.5 and 1 kW,

TABLE I
EV AND STORAGE (ESS) CONFIGURATION

Type	Capacity (kWh)	Min Capacity (kWh)	Max Charging (kW)	Max Discharging (kW)
ESS	6.4, 6.3, 10.0	0.32, 0.32, 0.5	2.0, 2.0, 2.5	2.0, 2.0, 2.5
Centralized ESS	2500	500	740	740
EV	90, 85, 70, 60, 24	9, 8.5, 7.0, 6.0, 2.4	9, 9, 9, 8, 3	6, 6, 6, 5, 2.5

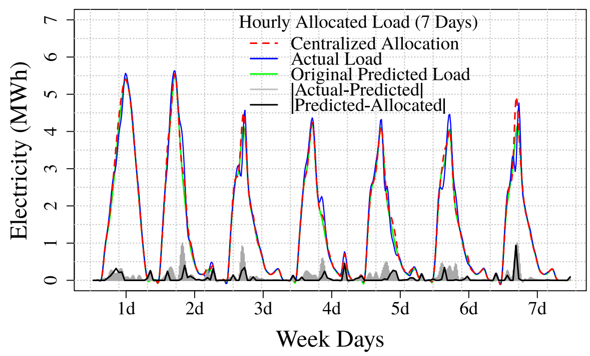

Fig. 2. Electricity allocated by the centralized method.

and the long-term RES generation during a day and forecast is presented in [11]. Both EV and ESS (such as Tesla, Nissan, Toshiba, Toyota, etc.) configurations are assumed as shown in Table I. The arrival and departure times, and consumption (kWh/km) while driving are assumed as discussed in Section III-D. For electricity price, we assume the values of coefficients a, b, and c to be 0.0001, 0.0001, and 0.05, respectively. We also assume the penalty (Q) for each kWh is 0.01 \$. To compare the RDCDSM method with an existing decentralized EV charge control, we consider noncooperative game (DECCG) [31] based allocation method with RESs. We also modify the DECCG to add household load and ESS. In this case, the ESS uses the same charging strategy as described in [31]. The modification of the existing energy allocation by controlling the EV charging is described in more detail in [11]. Finally, we use CPLEX and Java to develop the simulation program and execute the simulation on a desktop computer running Linux OS with 8 GB RAM, Intel Core i7 processor.

B. Numerical Results

Fig. 2 presents the predicted (unmodified) load, actual load, and hourly electricity delivery by the centralized method to all 1000 customers throughout the days of a week. In all cases, the centralized allocation system modifies the actual load by exploiting the RESs, ESSs, MESS, and EVs to match with the originally predicted demand, and hence avoid penalties. Therefore, the differences between the predicted demand and allocated (modified actual) electricity are minimized (see the gray and black curves in Fig. 2). The average difference between predicted and actual load was 0.1164591 MW/h (total 19.56513 MWh) without using the centralized method, whereas in the case of the centralized method, the difference was 0.04791264 MW/h (total

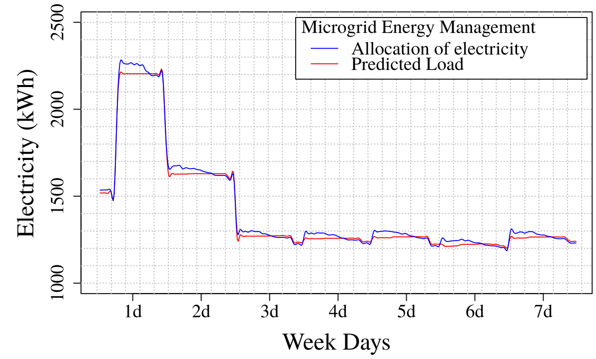

Fig. 3. RDCDSM: Electricity allocation.

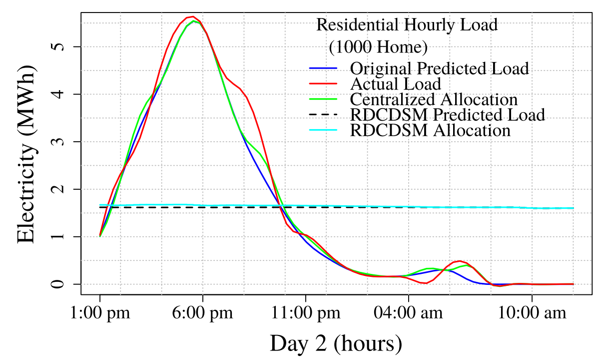

Fig. 4. RDCDSM versus centralized methods.

8.049323 MWh). The centralized method mitigates and reduces this difference by utilizing RES, ESSs, MESS, and rescheduling charging and discharging of EVs to carry (shift) electricity from one duration to another, and hence modifies the actual demand to match with the predicted load. Unfortunately, the centralized allocation is not planned based on a flattened load curve and hence does not reduce the electricity cost for the consumers (see Fig. 5). Fig. 3 shows the day ahead of RDCDSM prediction and online real-time allocation of electricity to all 1000 customers for seven consecutive days. Initially, we assume the EVs' stored energy is minimal; therefore, the load at day 1 is higher than any other days of the week. Our RDCDSM first flattens the demand for a day ahead prediction and, during the allocation phase, it satisfies the actual real-time need (see Fig. 2) by exploiting storage systems (by deciding their best strategies) while mitigating the gap between predicted and actual demands. Indeed, deciding best strategies (for storage systems) to meet the demand will avoid the purchase of energy, by the operator, at higher costs (to satisfy the actual demand) and hence reduces the cost of electricity to consumers. RDCDSM will effectively deal with load uncertainties in the system as it continuously and in real-time decides strategies for energy storage to mitigate discrepancies between forecast and actual loads. Fig. 4 (day 2 of Figs. 2 and 3) illustrates the results clearly for a day where both the RDCDSM and centralized allocation try to match the distribution to the predicted demand. The power delivery in the centralized method varies whereas, and as expected, the RDCDSM method results in a flat load curve. This is because in case of the centralized method, we use originally anticipated load as the customers

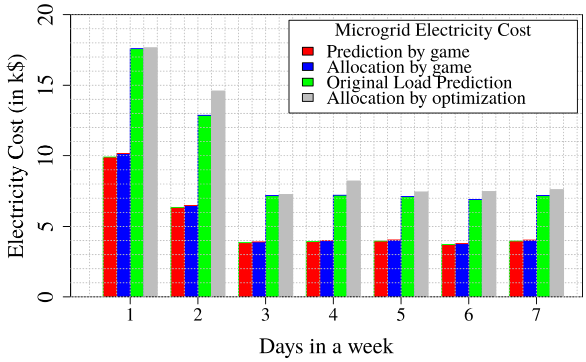

Fig. 5. Electricity cost: RDCDSM versus centralized.

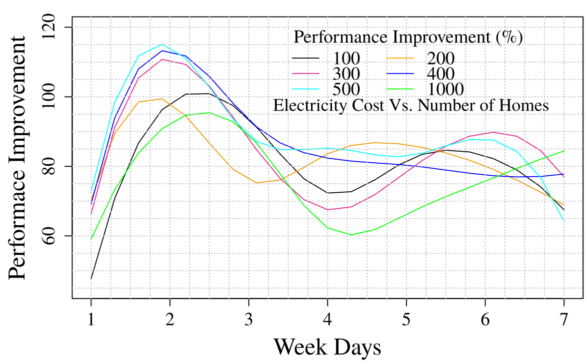

Fig. 6. RDCDSM versus centralized: Performance improvement.

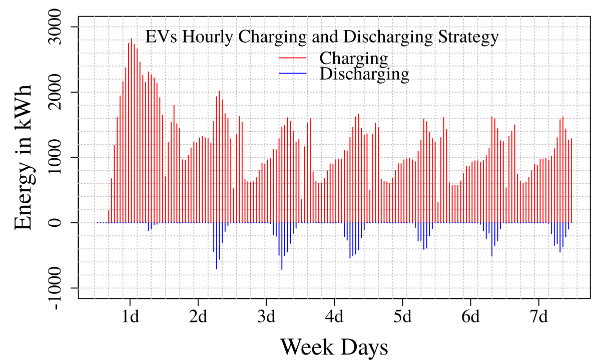

Fig. 7. RDCDSM: EVs charging and discharging strategy.

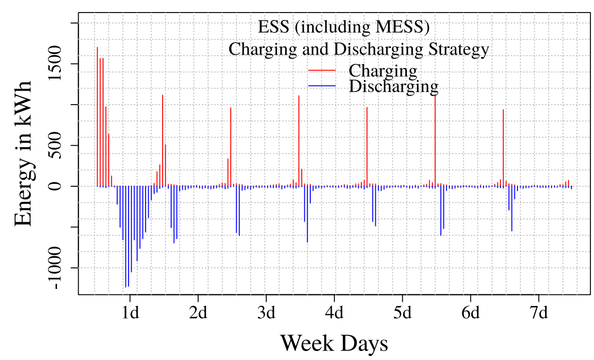

Fig. 8. RDCDSM: ESSs charging and discharging strategy.

predicted demand without any further refinement, whereas RDCDSM refines the projected demand to follow the flatten load curve; both approaches, however, exploit ESSs, EVs, RES, and MESS to modify the actual load to follow the predicted demand. It should be noted that the centralized method took days and weeks (sometimes may take months) to produce the result for a large microgrid, whereas RDCDSM required less than a minute to obtain the solution. Additionally, the centralized method may suffer from potential privacy issues as it requires customers' detail consumption patterns and load profiles for the optimization and allocation of electricity. Whereas in RDCDSM, consumers locally decide their best strategies, without sending information to the operator. Fig. 5 compares the total cost of electricity for the days of the week, determined by the proposed RDCDSM and centralized allocation methods. In all cases, the electricity cost is lower in RDCDSM than that determined by the centralized method. Indeed, RDCDSM starts off by flattening the projected load curve and hence making it price-aware, by having the consumers play a strategic game to forecast their demands. Alternatively, one observes peaks and valleys in the curve demand for the centralized method (e.g., see Fig. 4), which yields higher electricity prices. As mentioned, both methods exploit the ESSs to compensate for any deficit between actual load and predicted demand; however, since the load is already flattened in phase 1 by RDCDSM, it is easier and more cost-effective for the operator to mitigate the differences between the two without imposing higher costs on the consumers. The performance improvement of the RDCDSM compared to the centralized method is depicted in Fig. 6 for various microgrid sizes. In all cases, the proposed system performed better. In Fig. 6, it is found that the performance of RDCDSM increases when the load is high and decreases when the load is low. This is because the system becomes more flexible in high load conditions, thereby RDCDSM redistributes loads and power more smoothly.

Figs. 7 and 8 demonstrate the charging and discharging strategies of EVs and ESSs (including MESS) in RDCDSM. The integration of RES is an important objective for the modern power grid. Unfortunately, the renewable energy is intermittent in nature as it is dependent on weather conditions. One of the solutions to integrate RES into the grid is likely by utilizing ESSs and EVs, but ESSs and EVs have limited capacity. Hence, an intelligent system such as RDCDSM enables to store and re-use renewable energy by exploiting ESSs and EVs optimally. The red and blue lines in Figs. 7 and 8 demonstrate the charging and discharging patterns of ESSs and EVs. When we observe Figs. 7 and 8, we find that the charging of ESSs and some of the EVs are scheduled when the generation from RES is high (daytime) and discharging when load is high (evening) or when there is no generation. This is an important feature of RDCDSM system which balances the microgrid load through the time against uncertainties arising from load and renewable energy. Fig. 9 represents the penalty imposed by the microgrid to those customers requesting more or less quantity of electricity compared to the proposed day ahead predicted demand. The penalty is lower in RDCDSM compared to the centralized scheme. This is because the load was not properly spread across time in the original prediction; furthermore, a fraction of the renewable energy may end up not being exploited due to lack of storage

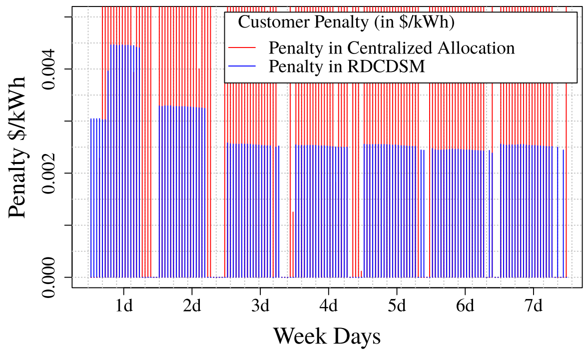

Fig. 9. Penalty imposed to customers.

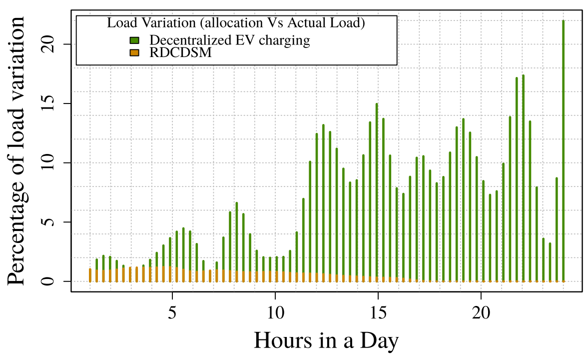

Fig. 10. DECCG versus RDCDSM: Hourly load variation.

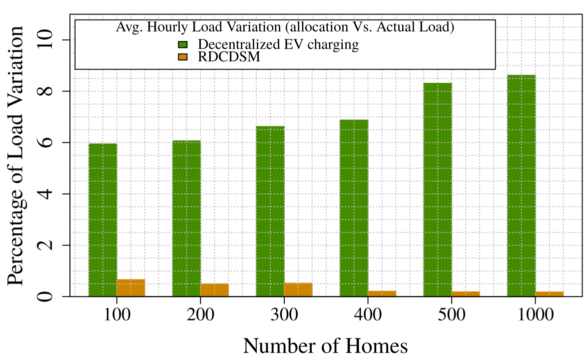

Fig. 11. Load variation and number of homes: DECCG versus RDCDSM.

space (as a result of the determined strategy). Furthermore, at time of allocation (centralized/distribution system), and due to capacity and other constraints, the ESSs and EVs may not collectively supply enough energy to time slots where demand is very high. On the other hand, RDCDSM system uses ESSs and EVs optimally such that RES energy can be used properly. It is also found that the penalty is higher in high load duration in comparison to light load periods. This is evident because the actual demand changes more at high loads compared to low or moderate load durations.

Figs. 10 and 11 present the comparison between DECCG [31] and RDCDSM allocation of hourly demand for a day and daily average hourly demand for $100, 200, \ldots, 500, 1000$ homes. For all the cases, DECCG day-ahead schedule for consumption and actual need vary more compared to the proposed RDCDSM allocation. This is because DECCG method plans load for electricity consumption for a day ahead and does not have any option to adjust the electricity use to match the real demand. Whereas RDCDSM schedules electric loads for a day ahead and plan to produce electricity accordingly; next, it allocates power for the immediate need and reschedules the forecast load to match with the production plan for the rest of the day. Hence, the use of DECCG for load scheduling and electricity allocation will leave the grid more unstable and may need an additional generation to fulfill the real demand. In the case of RDCDSM, the allocated electricity for the load varies slightly (nearly 1%, see Figs. 11 and 10) from the planned production. This is possible because the RDCDSM exploits EV, ESS to store excess energy produced from RES and reschedule EV's consumption when the demand is low. In the case of DECCG, the hourly load (see Fig. 10) and the actual demand varies more than 10% in some cases which may not be suitable for the stability of the grid. Similar methods for day-ahead scheduling were discussed in [32]; we believe that it will produce the same results as DECCG. The adaptive electricity allocation in [33] allocates electricity using Lyapunov optimization to ensure quality of service of electricity. Unfortunately, the adaptive method does not count on the stability of the generation of electricity.

We believe that the variation in planning production and actual consumption will be very low (see Figs. 10 and 11). The microgrid operator can evaluate the percentage of variation between planned and real need or allocated amount using historical (forecast and actual) data using the RDCDSM method and demand for excess energy from the grid and store it to the MGESS. This MGESS energy can be used to fulfill the need of the microgrid. To do so, the operator may add an extra amount of electricity in the storage when it determines the amount of production using RDCDSM.

VI. Conclusion

We developed a real-time distributed energy management RDCDSM system to mitigate the intermittent nature of the RESs and fulfill the demand of a residential microgrid. The proposed RDCDSM processes the raw predicted load to produce a predicted load curve, balanced throughout time, for the microgrid and allocates electricity in real time in an intelligent way which reduces the gap between the predicted and distributed amount of power. Hence, the proposed system forces customers to collectively produce a flat load profile and stick to that profile at the time of actual consumption by means of a penalty. RDCDSM eases the integration of RESs with the grid by exploiting ESSs and EVs. We also developed a centralized allocation method to allocate electricity according to the day ahead simple prediction method to evaluate the performance of RDCDSM. The RDCDSM system took less time (less than a minute) to produce the results, whereas the centralized scheme needs days (and sometimes weeks) to provide a solution for a large microgrid. The proposed system requires more sensible equipment (HEMS), whereas the centralized system required a less intelligent system in the user premises. The centralized system, however, needs detailed information of consumption from users which may violate their privacy.

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