Distributed Home Energy Management System With Storage in Smart Grid Using Game Theory

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***Abstract*—In this paper, the problem of distributed home energy management system with storage (*HoMeS*) in a coalition, which consists of multiple microgrids and multiple customers, is studied using the *multiple-leader–multiple-follower Stackelberg game* theoretic model—a multistage and multilevel game. The microgrids, which act as the leaders, need to decide on the minimum amount of energy to be generated with the help of a central energy management unit and the optimum price per unit energy to maximize their profit. On the other hand, the customers, which act as the followers, need to decide on the optimum amount of energy to be consumed, including the energy to be requested for storage. Using the proposed distributed scheme, i.e., *HoMeS*, the earned profit of the grid improves up to 55%, and the customers consume almost 30.79% higher amount of energy, which, in turn, increases the utilization of the generated energy by the microgrids.**

***Index Terms*—Energy management, extensive game, microgrid, multiple-leader–multiple-follower Stackelberg game, smart grid, storage.**

I. Introduction

To achieve high reliability in power systems, traditional electrical grids need to be designed as modernized electrical systems, termed as *smart grids*. A smart grid [1]–[3] is visualized to be a cyberphysical system equipped with sustainable models of energy production, distribution, and usage [4]. It also integrates several advanced techniques such as advanced metering infrastructure, automatic meter reading, distributed energy resources, energy management systems, intelligent electronic devices, and plug-in hybrid electrical vehicles (PHEVs) [2]. Unlike in existing power systems, in which electricity is distributed unidirectionally to the customers by the main grid having a centralized system, in a smart grid with duplex-communication infrastructure, the large-scale traditional electrical grid is divided into microgrids [5], having bidirectional electricity exchange facility with the substation, and the main grid. In the presence of several microgrids, it is desirable to allow a group of microgrids to service a group of customers based on their demands in a distributed manner, so as to relax the load on the main grid. One of the important features in a smart grid is the demand-side energy distribution, which gives the opportunity for flexible energy demand according to the requirements of the customers.

The microgrids generate energy using renewable energy resources such as wind power, solar energy [3], and hydro power [6]. Hence, the amount of generated energy is not fixed at different times in a day. If the total energy demand by the customers the total generated energy by that microgrid, it requests the main grid to supply the deficient amount of energy. As the requested energy by the customers to each microgrid is discreet, the load on each microgrid does not remain the same in any specific time. During on-peak hours, the demand of the customers is higher than the demand during off-peak hours. Hence, in on-peak hours, the microgrids request the main grid to supply energy to fulfill the customers' demand, whereas in off-peak hours, the microgrids have excess amount of energy. In such a condition, the existence of storage capacity with the customers will be cost effective, and the reliability of the energy supply will also increase. Additionally, having storage facility at the customer end, in on-peak hours, the amount of requested energy by the customers will be reduced while the required energy can be served using stored energy. On the other hand, in off-peak hours, the customers consume a high amount of energy, including energy for storage. Moreover, we consider that each customer can communicate with multiple microgrids available with a coalition, to reduce energy loss.

In this paper, we introduce a *game-theoretic approach* for distributed home energy management system with storage (HoMeS). We use a multiple-leader–multiple-follower Stackelberg game to decide on the strategies for the microgrids to maximize their profit and proper utilization of generated energy and the strategies for the customers, so as to fulfill their energy requirement by maximizing their individual payoff values. Based on the remaining stored energy, each customer n decides on the required energy for the appliances, which is the minimum amount of requested energy for customer n, and broadcasts that information within the coalition. On receiving this information, the microgrids decide on the minimum energy to be generated and the minimum price per unit energy. The microgrid broadcasts the price per unit energy. Each customer decides the amount of energy to be requested, including the amount of energy for storage for future use. Each microgrid m decides on the price per unit energy based on the amount of requested energy using a noncooperative approach. In summary, our contributions in this paper are as follows.

a) We present the *HoMeS* model for real-time energy consumption of customers in the presence of storage facilities and several microgrids in a coalition.

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b) The multiple-leader–multiple-follower Stackelberg game-theoretic approach is used to evaluate the optimal strategies of the microgrids using a cooperative game, which is the initial phase of the proposed game, and the optimal strategies of the customers using a noncooperative game, which is the next phase of the proposed game.
c) We present three different algorithms. The first algorithm is used in the *Initialization Phase* (IP) for the microgrids to determine the minimum amount of energy to be generated. The second algorithm is used by the customers to decide on the amount of requested energy based on the real-time price of energy. In the final proposed algorithm, the microgrids decide on the price per unit energy on a real-time basis, depending on the total amount of requested energy.

The remainder of this paper is organized as follows. We briefly present the related literature in Section II. Section III describes the system model. In Section IV, we formulate the game-theoretic method using the multiple-leader–multiple-follower Stackelberg game and, thereafter, discuss its properties, and we also propose the distributed algorithms and discuss their performance in Section V. Finally, we conclude this paper while citing few research directions in Section VI.

II. Literature Review

In the last few years, a lot of research works on smart grids have emerged, viz., [7]–[18]. Some of the existing literatures are discussed in this section. Saad *et al.* [7], [8] formulated a coalition game having multiple microgrids and proposed a distributed algorithm for forming the coalition, assuming that one microgrid can exchange excess energy with the main grid [7] or other microgrids having deficiency of energy [8]. In case of power exchange between the microgrid and the main grid, there will be loss of energy over the distribution line. Bakker *et al.* [12] proposed a distributed load management system with a dynamic pricing strategy and have modeled it as a network congestion game. Misra *et al.* [14] proposed a distributed dynamic pricing mechanism for charging PHEVs. They used two different pricing schemes such as the home pricing scheme and the roaming pricing scheme. Molderink *et al.* [15] proposed an algorithm by using the energy in the off-peak and on-peak hours, with a virtual power plant. However, none of these works consider the storage issue in the customer side.

Fang *et al.* [17] proposed different energy management schemes. However, residential energy management system and bill reduction are studied without considering the impact of stored energy on the customers. Erol-Kantarci and Mouftah [18] proposed a time-to-use-aware energy management scheme. In this scheme, a customer consumes energy according to the time, i.e., an on-peak hour or an off-peak hour. In the on-peak hour, the customer has to wait for being served. Otherwise, the customer demands the required energy without waiting, if the delay is greater than the maximum allowable delay. However, the energy management policy adopted by the customers and the microgrids need further research to have an optimal solution and with minimum delay and less message overhead.

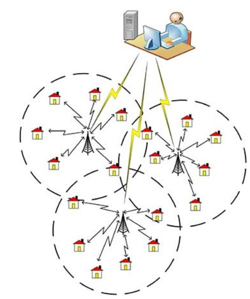

Fig. 1. Schematic diagram of the energy management system.

In the existing literature, several energy generation and consumption models are also proposed, by considering different uncertainties that impose imbalance costs to the system operators [19]. Some of the existing literatures are discussed here. Soroudi *et al.* evaluated the effect of renewable distributed generation units on active losses and distribution network in load supply with uncertainties using a fuzzy evaluation tool [20] and operation of distributed generation units on distribution networks [21].

In contrast to the existing works, a multistage stochastic game-theoretic model is used in this paper to characterize the effect of storage with the customers in the smart grid. We use the multiple-leader-multiple-follower Stackelberg game to develop the optimal solution for the home energy management system for each customer.

III. System Model

We consider an energy distribution system consisting of multiple microgrids and multiple customers. The schematic diagram of an energy management system is given in Fig. 1. In this, each customer has a smart meter and a communication unit. We consider a group of customers connected to a single microgrid. The total charging period in a day is divided into multiple time slots, i.e., T. In each time slot $t \leq T$, each microgrid, i.e., $m \in \mathcal{M}$, where $\mathcal{M}$ is the set of microgrids, has to decide on the amount of energy to be generated G_m^t for selling to the connected customers to meet their energy demand and maximizing its own revenue. The total energy generated in time slot t and the total energy generated by each microgrid $m \in \mathcal{M}$ in a day are denoted as G^t and G_m, respectively. Mathematically, we have

$$G^t = \sum_{m=1}^{m \in \mathcal{M}} G_m^t \text{ and } G_m = \sum_{t=1}^{T} G_m^t. \quad (1)$$

A group of microgrids $\mathcal{W} \subseteq \mathcal{M}$ forms a coalition Co_w, where $w \in (0, (|\mathcal{M}|/|\mathcal{W}|)]$, and serves a small geographical area, i.e., $\mathcal{A}_w$, consisting of a group of customers $\mathcal{C}_w \subseteq \mathcal{N}$, where $\mathcal{N}$ is the set of N number of customers, and $\mathcal{C}_w$ is the set of customers under coalition Co_w. Within a coalition, the microgrids can exchange energy between themselves.

Each customer $n \in \mathcal{N}$ requests a certain amount of energy e_n from its service provider, i.e., the corresponding microgrid, to fulfill its energy requirement, i.e., the energy requirement for the appliances of customer n, a_n, and the energy requirement for storage, x_n. Therefore

$$e_n = a_n + x_n, \qquad \forall\, n \in \mathcal{N}. \tag{2}$$

The demanded energy, i.e., e_n, of customer n may vary in different time slots, as the energy requirement of a customer n is based on different parameters such as the maximum storage capacity, $E_{\max}$; the amount of remaining stored energy, E_{res}; the price per unit energy decided by the service provider; the energy required for daily appliances, a_n; and the energy required for storage, x_n. We assume that the energy requirement for daily appliances, i.e., a_n, is known to the microgrids on a day-ahead basis, and the microgrid has to supply a_n amount of required energy. Therefore, in a coalition Co_w having $\mathcal{W}$ microgrids, the total amount of energy that has to be generated is at least $\sum_{n=1}^{n\in\mathcal{C}_w} a_n$. Mathematically, we have

$$\left[\arg\min \sum_{m=1}^{m\in\mathcal{W}} G_m \geq \sum_{n=1}^{n\in\mathcal{C}_w} a_n\right] \text{ and } \left[\sum_{m=1}^{m\in\mathcal{W}} G_m \geq \sum_{n=1}^{n\in\mathcal{C}_w} e_n\right]. \tag{3}$$

Hence, the net available energy for storage $\mathcal{S}_w$ in a coalition Co_w having $\mathcal{W}$ microgrids is given by

$$\mathcal{S}_w = \left(\sum_{m=1}^{m\in\mathcal{W}} G_m - \sum_{n=1}^{n\in\mathcal{C}_w} a_n\right). \tag{4}$$

Since the net available energy $\mathcal{S}_w$ is fixed for the customers, the demands for storage of a customer n, i.e., x_n, has to satisfy the following condition:

$$\sum_{n=1}^{n\in\mathcal{C}_w} x_n \leq \mathcal{S}_w. \tag{5}$$

Based on the total energy requirement of the appliances in a coalition Co_w, i.e., $\sum_{n=1}^{n\in\mathcal{C}_w} a_n$, the microgrids need to decide among themselves on the minimum amount of energy, i.e., $G_{\min}$, required to be generated and the minimum price per unit energy, i.e., $p_{\min}$, to optimize the overall revenue of the microgrids. To provide the minimum energy requirement of each customer n, i.e., a_n, each microgrid decides $p_{\min}$ with the cooperation of other microgrids. Each microgrid m tries to sell the excess amount of generated energy with a higher price to maximize its revenue. Hence, an optimal price, which is neither too high nor too low, needs to be chosen by each microgrid, to maximize its profit.

To complete energy trading successfully, a proper interaction among the central energy management unit (CEMU), the microgrids, and the customers is needed. We divide the interactions into two stages—*IP with cooperation* (IPC) and *finalization phase with noncooperation* (FPN). In IPC, each microgrid m exchanges information with the CEMU to decide on $G_{\min}$ and $p_{\min}$. In FPN, each customer n in a coalition Co_w needs to decide on the amount of energy to be requested to microgrid m, and the microgrid m needs to decide on the price per unit energy p_m, where $p_m \geq p_{\min}$. However, p_m also depends on e_n and the number of customers under microgrid m, i.e., $|\mathcal{C}_m|$. If the amount of energy acquired for appliances is higher, the excess energy for storage, i.e., $\mathcal{S}_w$, will be reduced.

The energy requested by each customer has to fulfill the constraints given in (3). It is also to be noted that the price decided by a microgrid is also dependent on the amount of requested energy. Thus, the main challenges faced to develop the approach that can capture the two stages of decision-making processes are as follows.

i) Modeling the decision-making processes, the interactions between the microgrids and the CEMU, and the microgrids and the customers in the network, subject to the constraints in (3).
ii) Developing an algorithm for the microgrids to decide on $G_{\min}$ and $p_{\min}$, by having an interaction with the CEMU.
iii) Developing another algorithm for the microgrids to decide on the amount of energy to be generated and the actual price per unit energy p_m.
iv) Each customer n needs to decide on the total amount of energy e_n based on the optimally decided amount of energy for storage x_n to maximize its storage satisfaction level.

IV. Proposed Multiple-Leader–Multiple-Follower Stackelberg Game

A. Game Formulation

To study the interactions between the microgrids and the customers, as mentioned earlier, we use a multiple-leader–multiple-follower Stackelberg game. This is a multistage and multilevel game, where a group of players, i.e., the followers, takes a decision based on the decision of the leaders, using a noncooperative game, and the leaders make a decision among themselves using a cooperative game. In this paper, we consider the microgrids as the leaders and the customers as the followers. Hence, in the IP, the microgrids need to decide $G_{\min}$, and $p_{\min}$, using a cooperative game-theoretic approach. In the FP, the customers need to decide e_n, and the microgrids need to decide on the price per unit energy, i.e., p_m, using a noncooperative game-theoretic approach. The overall game is defined by using the strategic form: $\Upsilon = \{(\mathcal{N} \cup \mathcal{M}), (X_n, A_n, E_n, \psi_n)_{n\in\mathcal{N}}, (G_m, P_m, \varphi_m, p_m, \phi_m)_{m\in\mathcal{M}}, G_{\min}, p_{\min}\}$.

The components in the strategic form Υ are as follows.

i) Each customer n acts as a follower in the game and needs to decide on the optimum energy demand e_n, based on the optimum price decided by the microgrid.
ii) The strategy of each customer n is to decide e_n, while satisfying the constraints given in (3) and (5).
iii) Each customer n optimizes the amount of energy to be stored, while satisfying the constraint— $\mathcal{S} \geq \sum_{n=1}^{n\in\mathcal{N}} x_n$, where $\mathcal{S}$, which is broadcasted to the customers within a coalition by the CEMU, is the total amount of excess energy. Mathematically,

$$\mathcal{S} = \sum \mathcal{S}_w. \tag{6}$$

iv) The utility function $\psi_n(\cdot)$ of a customer n is used to maximize the payoff value by capturing the benefit of the total consumed energy e_n.

v) The utility function $\varphi_m(\cdot)$ of a microgrid m is used to maximize the payoff value of microgrid m using the information of total consumed energy from microgrid m.

vi) The price p_m denotes the price per unit energy decided by microgrid m.

vii) The utility function ϕ_m of a microgrid m captures the minimum profit by selling the energy to fulfill the minimum energy requirement by the customers $\mathcal{C}_w$ in a coalition Co_w.

viii) The energy $G_{\min}$ denotes the minimum energy needed to be generated by each microgrid m.

The game formulation of the IP and the FP of the multiple-leader–multiple-follower Stackelberg game is discussed in Section IV-A1 and 2, respectively.

1) Game Formulation for the IP:

a) Utility function of a microgrid for the IP: In the IP, each microgrid m, which acts as a leader, decides on $G_{\min}$ and $P_{\min}$, based on the minimum amount of requested energy by the customers, i.e., $a_n; \forall\, n \in \mathcal{C}_w$.

Initially, in a coalition Co_w, each customer n calculates its expected amount of energy vector, i.e., A_n, and broadcasts to the microgrids, i.e., $\mathcal{W}$. The microgrid $m \in \mathcal{W}$ decides to generate g_m amount of energy to maximize its utility function $\phi_m(g_m, \mathbf{g}_{-m})$, whereas $p_{\min}$ would be fixed for all the microgrids in a coalition. Mathematically,

$$\arg\max_{g_m} \phi_m(g_m, \mathbf{g}_{-m}), \qquad \forall\, m \in \mathcal{W} \tag{7}$$

where $\mathbf{g}_{-m} = \{g_1, g_2, \ldots, g_{m-1}, g_{m+1}, \ldots, g_{|\mathcal{W}|}\}$. Equation (7) must satisfy the constraint given in (3). Hence, the properties that the utility function must satisfy are as follows.

i) The utility function of a microgrid m, i.e., ϕ_m, is considered as a nondecreasing function. With the increase in energy demand, the total revenue of a microgrid m increases. Mathematically,

$$\frac{\delta\phi_m(g_m, \mathbf{g}_{-m})}{\delta g_m} \geq 0, \qquad \forall\, m \in \mathcal{W} \text{ and } \forall\, n \in \mathcal{C}_w. \tag{8}$$

ii) If the total generated energy by a microgrid m is equal to the total requested energy by a group of customers, i.e., $\sum_{n=1}^{n\in\mathcal{C}_w} a_n$, the utility function is considered to be in the marginal position. In this situation, the utility function of the microgrids is considered to be a nonincreasing function. Mathematically,

$$\frac{\delta^2\phi_m(g_m, \mathbf{g}_{-m})}{\delta {g_m}^2} < 0, \qquad \forall\, m \in \mathcal{W}. \tag{9}$$

iii) With the increase in the total amount of energy demand by the customers, i.e., $\sum_n a_n$, the payoff of the utility function ϕ_m increases. Mathematically,

$$\frac{\delta\phi_m(g_m, \mathbf{g}_{-m})}{\delta a_n} > 0, \qquad \forall\, m \in \mathcal{W}, \text{ and } \forall\, n \in \mathcal{C}_w. \tag{10}$$

iv) With a fixed amount of energy request, i.e., $\sum_n a_n$, if the price per unit energy p_m increases, the payoff of the utility function ϕ_m also increases. Mathematically,

$$\frac{\delta\phi_m(g_m, \mathbf{g}_{-m})}{\delta p_m} > 0, \qquad \forall\, m \in \mathcal{M}. \tag{11}$$

The utility function ϕ_m denotes the maximum profit of microgrid m by selling the minimum amount of energy. Therefore, the utility function ϕ_m becomes

$$\phi_m(g_m, \mathbf{g}_{-m}) = p_m g_m - c_m g_m \tag{12}$$

where c_m is the generation cost per unit energy for microgrid m. The total energy that needs to be generated by the microgrids $\mathcal{W}$ in a coalition, i.e., $\mathcal{G}_\mathcal{W}$, is defined as

$$\mathcal{G}_\mathcal{W} = \sum^{m\in\mathcal{W}} g_m. \tag{13}$$

b) Existence of GNE for the IP: In any optimization approach, there should be an optimal or Pareto-optimal solution. Therefore, we need to investigate the existence of a generalized Nash equilibrium (GNE) for the IP. In this phase, we find out the equilibrium point under the following assumptions: In a coalition, 1) each microgrid has the same generation cost per unit energy, i.e., c, and 2) $p_{\min}$ would be fixed for all the microgrids.

Definition 1: While the total demand of energy for all the customers is fixed, with the increase in supply of the total amount of energy, the price per unit energy reduces. Hence, the price function inversely varies with the demand function. We formulate an inverse demand function $\mathcal{P}(\mathcal{G}_\mathcal{W})$ as follows:

$$\mathcal{P}(\mathcal{G}_\mathcal{W}) = A - \mathcal{G}_\mathcal{W} \tag{14}$$

where A is a constant, and $\mathcal{G}_\mathcal{W}$ is the total generated energy by $\mathcal{W}$ microgrids. $\mathcal{G}_\mathcal{W}$ must satisfy the condition given in (3).

Theorem 1: If the generation cost per unit energy for each microgrid is the same, the amount of energy to be generated by each microgrid m, i.e., g_m, will be the same, i.e., a GNE point, if and only if the following inequality holds:

$$\phi_m\left(g_m^*, \mathbf{g}_{-m}^*\right) \geq \phi_m\left(g_m, \mathbf{g}_{-m}^*\right). \tag{15}$$

Proof: For the microgrids m, the generation cost per unit energy, i.e., c_m, remains the same. The optimal energy supply of microgrid m, i.e., the best response of microgrid m, is defined as follows:

$$g_m^*(c_m) = \arg\max_{g_m} \left((A - \mathcal{G}_\mathcal{W}) - c_m\right) g_m. \tag{16}$$

We rewrite the function by replacing c_m by c, where c is a constant. Therefore,

$$g_m^*(c) = \arg\max_{g_m} \left((A - \mathcal{G}_\mathcal{W}) - c\right) g_m \tag{17}$$

$$g_1^*(c) = \arg\max_{g_1} \left[\left(A - g_1 - g_2^* - \sum_{m=3}^{m\in\mathcal{W}} g_m^*\right) - c\right] g_1. \tag{18}$$

Similarly,

$$g_2^*(c)=\arg\max_{g_2}\left[\left(A-g_1^*-g_2-\sum_{m=3}^{m\in\mathcal{W}}g_m^*\right)-c\right]g_2. \quad (19)$$

The optimal value of g_1, i.e., g_1^*, can be obtained from the necessary condition, as follows:

$$\left.\frac{\delta g_1(c)}{\delta g_1}\right|_{g_1=g_1^*}=0; \quad \Rightarrow g_1^*=\frac{A-g_2^*-\sum\limits_{m=3}^{m\in\mathcal{W}}g_m^*-c}{2}. \quad (20)$$

Similarly, we get the optimum value of g_2 as follows:

$$g_2^*=\frac{A-g_1^*-\sum\limits_{m=3}^{m\in\mathcal{W}}g_m^*-c}{2}. \quad (21)$$

By solving (20) and (21), we get

$$g_1^*=g_2^*=\cdots=g_m^*=\cdots=g_{|\mathcal{W}|}^*=A-c. \quad (22)$$

Hence, within a coalition, each microgrid m generates the same minimum amount of energy to satisfy the inequality for GNE. ■

2) Game Formulation for the FP: Initially, each leader, i.e., microgrid m, generates energy using renewable energy resources. Microgrid m needs to generate energy using non-renewable energy resources, if the microgrid does not satisfy the following inequality:

$$(G_{RE})_m \geq G_{\min} \quad (23)$$

where $(G_{RE})_m$ is the amount of energy generated using renewable energy resources. Therefore, we can define the amount of energy generated using non-renewable energy resources, i.e., $(G_{NE})_m$, as follows:

$$(G_{NE})_{m_{\min}}=\begin{cases}0, & \text{if } (G_{RE})_m \geq G_{\min}\\ G_{\min}-(G_{RE})_m, & \text{if } (G_{RE})_m < G_{\min}.\end{cases} \quad (24)$$

a) Utility function of a customer: For each customer $n\in\mathcal{C}_w$, we formulate the utility function $\psi_n(\cdot)$ to introduce the amount of energy requested by the customers. In the utility function ψ_n, the maximum energy storage capacity of customer n is denoted by $(E_{\max})_n$, the stored energy of a customer n is denoted by $(E_{res})_n$, the total amount of energy requested by customer n is denoted by e_n, and $\mathbf{e}_{-n}$ denotes the total amount of energy requested by the other customers, except customer n, i.e., $\mathbf{e}_{-n}=\{e_1,e_2,e_3,\ldots,e_{n-1},e_{n+1},\ldots,e_{|\mathcal{C}_w|}\}$, needed to be predicted by customer n, where $|\mathcal{C}_w|$ is the number of customers in a coalition Co_w. Each customer n intends to increase $(E_{res})_n$, as that can be used by her/him at the on-peak hour and also in a blackout or islanding situation. Hence, having a fixed amount of $(E_{\max})_n$, customer n requests higher e_n due to a higher amount of energy needed for storage x_n. The amount of energy requested for storage will be affected by the decided price per unit energy, i.e., p_m, by microgrid m. Thus, the property of the utility function $\psi_n(\cdot)$ of a customer $n\in\mathcal{C}_w$ must satisfy the following conditions.

i) The utility function ψ_n of customer n is considered as a nondecreasing function, as each customer wants to acquire more e_n to maximize $(E_{res})_n$. Mathematically,

$$\frac{\delta\psi_n\left(e_n,\mathbf{e}_{-n},(E_{\max})_n,(E_{res})_n,p_m\right)}{\delta e_n}\geq 0. \quad (25)$$

ii) The limiting value of the utility function ψ_n of a customer n is considered to be a nonincreasing function, as $(E_{res})_n$ increases the amount of e_n. Mathematically,

$$\frac{\delta^2\psi_n\left(e_n,\mathbf{e}_{-n},(E_{\max})_n,(E_{res})_n,p_m\right)}{\delta {e_n}^2}<0. \quad (26)$$

iii) If $(E_{\max})_n$ is higher, the energy requirement of customer n will be higher. Hence, the utility function ψ_n proportionally varies with $(E_{\max})_n$. Mathematically,

$$\frac{\delta\psi_n\left(e_n,\mathbf{e}_{-n},(E_{\max})_n,(E_{res})_n,p_m\right)}{\delta(E_{\max})_n}>0. \quad (27)$$

iv) If $(E_{res})_n$ decreases, the energy requirement of customer n increases. The utility function ψ_n has an inversely proportional relationship with $(E_{res})_n$. Mathematically,

$$\frac{\delta\psi_n\left(e_n,\mathbf{e}_{-n},(E_{\max})_n,(E_{res})_n,p_m\right)}{\delta(E_{res})_n}<0. \quad (28)$$

v) The amount of e_n, is affected by p_m decided by microgrid m. With the higher value of price, the payoff of the utility function ψ_n of a customer n decreases. Mathematically,

$$\frac{\delta\psi_n\left(e_n,\mathbf{e}_{-n},(E_{\max})_n,(E_{res})_n,p_m\right)}{\delta p_m}<0. \quad (29)$$

Therefore, the utility function ψ_n is formulated as follows:

$$\psi_n(\cdot)=(E_{\max})_n e_n-\frac{1}{2}\alpha\frac{(E_{res})_n}{(E_{\max})_n}{e_n}^2-\beta\frac{p_m}{p_{\min}}\mathcal{S}_w e_n. \quad (30)$$

We consider that the transmission channel is ideal in nature, i.e., the resistance of the transmission channel is considered to be zero. Therefore, the transmission losses due to energy transfer are zero. Additionally, we consider that the energy transmission limit is taken cared of by electrical circuitry, i.e., the transformers. Hence, $\psi_n(e_n,\mathbf{e}_{-n},(E_{\max})_n,(E_{res})_n,p_m)$ must satisfy the following constraints.

1) e_n is defined in (2).

2) The amount of a_n requested by customer n satisfies

$$a_n \in \left[0, \sum_{m=1}^{m\in\mathcal{W}} g_m - \sum_{q=1,q\neq n}^{q\in\mathcal{C}_w} a_q\right]. \quad (31)$$

3) The amount of x_n requested by customer n satisfies

$$x_n \in \left[0, \sum_{m=1}^{m\in\mathcal{W}} g_m - \sum_{r=1}^{r\in\mathcal{C}_w} a_r - \sum_{q=1,q\neq n}^{q\in\mathcal{C}_w} x_q\right] \text{ and } \sum_{n}^{n\in\mathcal{C}_w} x_n \leq \mathcal{S}_w. \quad (32)$$

4) α and β are constants and have a fixed value within a coalition. These constants satisfy the following inequality:

$$\alpha, \beta > 0. \quad (33)$$

b) Utility function of a microgrid: Each microgrid $m \in \mathcal{W}$ gets a revenue of $p_m e_n$ by selling e_n amount of energy with p_m price per unit energy. Mathematically,

$$\varphi_m\left(e_n(p_m), p_m\right) = p_m \sum_n e_n \quad (34)$$

where p_m is the fixed price per unit energy for microgrid m. However, each microgrid knows that if the value of p_m is lower, the amount of energy requested by the customers is higher, and vice versa; in either case, it may get less revenue. Hence, microgrid m needs to choose an optimized value of p_m to maximize its revenue. Mathematically,

$$\arg\max \varphi_m\left(e_n(p_m), p_m\right) = \max_{p_m} \sum_m \sum_n p_m e_n \quad (35)$$

where $m \in \mathcal{W}$, $\mathcal{W} \subseteq \mathcal{M}$, and $p_m \geq p_{\min}$.

The requested energy e_n of customer n is dependent not only on p_m and the amount of required energy to fulfill its maximum storage capacity, i.e., $((E_{\max})_n - (E_{res})_n)$, but also on the requested energy by the other customers. Therefore, this scenario leads to a noncooperative game that deals with sharing a common product having a fixed constraint for all. We will prove in Section IV-A2 that there exists a GNE.

Definition 2: The set of strategies $(\{e_n^*\}_{n\in\mathcal{N}}, \{p_m^*\}_{m\in\mathcal{M}})$ is considered as the GNE solutions, if those satisfy the following inequalities:

$$\psi_n\left(e_n^*, \mathbf{e}_{-n}^*, \cdot, p_m^*\right) \geq \psi_n\left(e_n, \mathbf{e}_{-n}^*, \cdot, p_m^*\right) \quad (36)$$

$$\varphi_m\left(e_n^*\left(p_m^*\right), p_m^*\right) \geq \varphi_m\left(e_n^*(p_m), p_m\right) \quad (37)$$

where e_n^* is the optimum energy requested by customer n, and p_m^* is the optimum price per unit energy decided by microgrid m. Each customer n cannot maximize the payoff of the utility function ψ_n by changing the value of e_n from the value of e_n^*. Similarly, each microgrid m cannot maximize the payoff of the utility function φ_m by choosing a higher price p_m than the price p_m^*.

c) Existence of GNE for the FP: We determine the existence of a GNE by showing that it satisfies the properties of *variation inequality* (VI), as it is used to get the optimum convex solution under some constraints of inequality.

Theorem 2: Given a fixed price p_m by microgrid m, there exists a GNE, as there exists a variational equilibrium for the utility function $\psi_n(e_n^*, \mathbf{e}_{-n}^*, (E_{\max})_n, (E_{res})_n, p_m^*)$.

Proof: In the FP, the utility function $\psi_n(\cdot)$ needs to be maximized. The utility function $\psi_{k,k\neq n}(\cdot)$, where $k \in \mathcal{C}_w$, also needs to be maximized, i.e.,

$$\psi_{k,k\neq n}(\cdot) = (E_{\max})_k e_k - \frac{1}{2}\alpha\frac{(E_{res})_k}{(E_{\max})_k}{e_k}^2 - \beta\frac{p_m}{p_{\min}}\mathcal{S}_w e_k. \quad (38)$$

From (30) and (38), we get

$$\psi(\cdot) = \sum_n (E_{\max})_n e_n - \frac{1}{2}\alpha\sum_n\frac{(E_{res})_n}{(E_{\max})_n}{e_n}^2 - \beta\frac{p_m}{p_{\min}}\mathcal{S}_w\sum_n e_n. \quad (39)$$

Using the method of Lagrangian multiplier, the *Karush–Kuhn–Tucker* (KKT) condition of customer n for the GNE problem becomes

$$\nabla_{e_n}\psi_n(\cdot) - \nabla_{e_n}\left(\sum_n x_n - \mathcal{S}_w\right)\mu_n = 0$$

$$\left(\sum_n x_n - \mathcal{S}_w\right)\mu_n = 0 \text{ and } \mu_n \geq 0 \quad (40)$$

where μ_n is the Lagrangian multiplier for customer n.

By using the property of VI, we get VI$(\mathbf{B}, \mathbf{X})$ as the solution of the variational equilibrium, where $\mathbf{X}$ is the set of optimum points for x, and $\mathbf{B} = \nabla_{e_n}\psi_n(\cdot)$. We get the Jacobian matrix of $\mathbf{B}$ as follows:

$$\mathbf{J_B} = \nabla_\mathbf{e}\mathbf{B} = \begin{bmatrix} (E_{\max})_1 - \alpha\frac{(E_{res})_1}{(E_{\max})_1}e_1 - \beta\frac{p_m}{p_{\min}}\mathcal{S}_w \\ \vdots \\ (E_{\max})_{|\mathcal{C}_w|} - \alpha\frac{(E_{res})_{|\mathcal{C}_w|}}{(E_{\max})_{|\mathcal{C}_w|}}e_{|\mathcal{C}_w|} - \beta\frac{p_m}{p_{\min}}\mathcal{S}_w \end{bmatrix}. \quad (41)$$

The Hessian matrix of $\mathbf{B}$ is the Jacobian matrix of $\nabla_\mathbf{e}\mathbf{B}$. Mathematically, we have

$$\mathbf{H_B} = \mathbf{J}(\nabla_\mathbf{e}\mathbf{B}) = \begin{bmatrix} -\alpha\frac{(E_{res})_1}{(E_{\max})_1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & -\alpha\frac{(E_{res})_{|\mathcal{C}_w|}}{(E_{\max})_{|\mathcal{C}_w|}} \end{bmatrix}. \quad (42)$$

As the Hessian matrix $\mathbf{H_B}$ is a diagonal matrix, we infer that vector $\mathbf{e}$ has a unique solution, where $\mathbf{e} = \{e_1, \ldots, e_{|\mathcal{C}_w|}\}$, and the variational equilibrium exists. Therefore, for a fixed price, there exists a GNE. ■

B. Why Stackelberg Game?

In HoMeS, the microgrids and the customers perform a sequential competition within themselves. Initially, the microgrids decide $p_{\min}$, based on a_n. On the other hand, the customers decide e_n, including the amount of x_n, based on the price p_m with initial condition $p_m|_{t=0}= p_{\min}$. Sequentially, the microgrids modify p_m based on the value of e_n. This process continues until the equilibrium point is reached. Hence, for modeling the proposed scheme, i.e., HoMeS, we use the multiple-leader–multiple-follower Stackelberg game.

C. Proposed Solution Approach

From Section IV-A, we get that a GNE exists for the multiple-leader–multiple-follower Stackelberg game-theoretic approach used in HoMeS. Here, we compute for the optimum solutions of the unknown variables.

a) Solution approach for the IP: In the IP, $G_{\min}$, and $p_{\min}$, are decided, where c is fixed for the microgrids $\mathcal{M}$.

Definition 3: In a coalition, $p_{\min}$ is the same as the generation cost per unit energy c. Mathematically,

$$p_{\min} = c, \qquad c > 0. \tag{43}$$

If for a microgrid m, p_m is the same as the generation cost c, i.e., $p_{\min}$, then the profit of microgrid m is equal to zero.

Lemma 1: In a coalition, each microgrid needs to generate the same minimum amount of energy to fulfill customers' energy demand.

Proof: From Theorem 1 and (13), we get

$$g_1^* = \frac{g_2^* + g_3^* + g_4^* + \cdots + g_{|\mathcal{W}|}^*}{|\mathcal{W}| - 1}. \tag{44}$$

We rewrite (44) as follows:

$$g_1^* = \frac{g_1^* + g_2^* + g_3^* + \cdots + g_{|\mathcal{W}|}^*}{|\mathcal{W}|} = \frac{\sum_{m=1}^{m\in\mathcal{W}} g_m^*}{|\mathcal{W}|}. \tag{45}$$

Therefore, the minimum energy to be generated by each microgrid m is the same, as given in (45). ■

b) Solution approach for the FP: Here, the value of the optimum amount of energy requested by customer n, i.e., e_n^*, given the fixed p_m, and the value of optimum price, i.e., p_m^*, for the given e_n^*, are computed.

For each customer n, solving the KKT condition for the GNE problem defined in (40) results in

$$(E_{\max})_n - \alpha\frac{(E_{res})_n}{(E_{\max})_n}e_n - \beta\frac{p_m}{p_{\min}}\mathcal{S}_w - \mu_n = 0. \tag{46}$$

From (40), we get $\mu_n \geq 0$. Therefore

$$(E_{\max})_n - \alpha\frac{(E_{res})_n}{(E_{\max})_n}e_n - \beta\frac{p_m}{p_{\min}}\mathcal{S}_w \geq 0. \tag{47}$$

Solving (48), we get

$$e_n \leq \frac{(E_{\max})_n}{\alpha(E_{res})_n}\left[(E_{\max})_n - \beta\frac{p_m}{p_{\min}}\mathcal{S}_w\right] \tag{48}$$

$$p_m \leq \frac{p_{\min}}{\beta\mathcal{S}_w}\left[(E_{\max})_n - \alpha\frac{(E_{res})_n}{(E_{\max})_n}e_n\right]. \tag{49}$$

Hence, the optimal values of e_n and p_m are as follows:

$$e_n^* = \frac{(E_{\max})_n}{\alpha(E_{res})_n}\left[(E_{\max})_n - \beta\frac{p_m^*}{p_{\min}}\mathcal{S}_w\right] \tag{50}$$

$$p_m^* = \frac{p_{\min}}{\beta\mathcal{S}_w}\left[(E_{\max})_n - \alpha\frac{(E_{res})_n}{(E_{\max})_n}e_n^*\right]. \tag{51}$$

D. Proposed Algorithm

In this paper, we propose two different algorithms: the IPC algorithm and the FPN algorithm. In the IPC algorithm, the customers provide their minimum energy consumption profile for appliances on a day-ahead basis. After getting the information, the microgrids communicate within themselves, i.e., cooperate, to finalize the values of $G_{\min}$ and $p_{\min}$. In the FPN algorithm, after getting $p_{\min}$, the customers communicate with the corresponding microgrids and decide e_n. After getting the actual consumption profile of the customers, each microgrid m decides p_m on a real-time basis. The microgrids again broadcast p_m, and the customers may change their strategies, i.e., the value of e_n. This iterative process is performed between the customers and the microgrids until equilibrium is reached. After reaching the equilibrium point, the microgrids broadcast the same price as in the previous iteration. Consequently, the amount of energy to be consumed by each customer gets fixed.

1) IPC Algorithm: Initially, each customer n broadcasts a vector A_n representing his/her energy consumption profile for the appliances. Based on that information, the microgrids decide on the amount of energy to be generated by each microgrid, as discussed in Algorithm 1. The microgrids also make an agreement within themselves to decide $p_{\min}$.

Algorithm 1 IPC algorithm for each microgrid

Input: A_n: Broadcast energy consumption vector
Outputs: $G_{\min}$: The minimum energy to be generated
$p_{\min}$: The minimum price per unit energy

while $\sum_{m=1}^{m\in\mathcal{W}} g_m < \sum_{n=1}^{n\in\mathcal{C}_w} a_n$
if $\phi_m(g_m^*, \mathbf{g}_{-m}^*) \ngeq \phi_m(g_m, \mathbf{g}_{-m}^*)$
1. Optimized value of g_m, i.e., g_m^* is found
else
2. Evaluate the amount of energy to be generated, $g_m^{modified}$
3. $g_m = g_m^{modified}$
end if
end while
4. Decide $p_{\min}$
5. Calculate minimum profit $= (p_{\min} - c)g_m$
while $(p_{\min} - c) < 0$
6. Decide higher value of $p_{\min}$, $p_m^{modified}$
7. $p_{\min} = p_m^{modified}$, is computed
end while

2) FPN Algorithm: In the FP, the customers and the microgrids execute two different algorithms, namely, Algorithms 2 and 3, respectively. The customers decide on the amount of

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Simulation area	20×20 km^2
Number of micro-grids	10
Number of Customers	1000
Minimum requested energy for appliances	90 MWh
Maximum requested energy for appliances	100 MWh
Customer's minimum storage capacity	35 MWh
Customer's maximum storage capacity	65 MWh
Customer's minimum residual stored energy	20 KWh
Minimum renewable energy generated	500 MWh
Maximum renewable energy generated	650 MWh
Generation cost	10-20 USD/MWh

energy to be requested, including the amount of energy for storage, based on the optimum price decided by the microgrids. The microgrids need to decide p_m, where $p_m \geq (p_m)_{\min}$.

Algorithm 2 FPN algorithm for a customer

Inputs: p_m^*: The optimum price per unit energy
$\mathcal{S}_w$: Total energy for storage
Output: e_n^*: Amount of energy to be served

1. Decide e_n^* by customer n
while $\psi_n(e_n^*, \mathbf{e}_{-n}^*, \cdot, p_m^*) \ngeq \psi_n(e_n, \mathbf{e}_{-n}^*, \cdot, p_m^*)$
2. $e_n = e_n^*$
3. Evaluate the modified value of energy to be requested, $e_n^{modified}$
4. $e_n^* = e_n^{modified}$
end while

Algorithm 3 FPN algorithm for a microgrid

Input: e_n^*: Amount of energy to be served
Output: p_m^*: The optimum price per unit energy

1. Decide p_m^* by microgrid m
while $\varphi_m(e_n^*(p_m^*), p_m^*) \ngeq \varphi_m(e_n^*(p_m), p_m)$
2. $p_m = p_m^*$
3. Evaluate the modified value of p_m, $p_m^{modified}$
4. $p_m^* = p_m^{modified}$
end while

V. Performance Evaluation

A. Simulation Settings

For performance evolution, we considered randomly generated values for the microgrids and the customers, as shown in Table I, on a MATLAB simulation platform. The microgrids form a coalition, based on the total energy requirement of the customers, the generation capacity of the microgrids as discussed in [9].

B. Benchmarks

The performance of the proposed scheme, i.e., HoMeS, is evaluated by comparing it with other energy management policies, such as the economics of electric vehicle charging (E2VC) [22] approach and the price taking user (PTU) [23] approach.

We hereinafter refer to these different energy management policies as HoMeS, E2VC, and PTU. Tushar *et al.* [22] proposed a game-theoretic approach with storage. Samadi *et al.* [23] proposed a home energy management system without storage. Although E2VC [22] has been used for the energy management system of the PHEVs, its authors did not consider any mobility model such as a random way-point model or a Gauss Markov mobility model for the PHEVs. Thus, we can improve the efficiency in the home energy management system by using our proposed approach, i.e., HoMeS, over E2VC and PTU.

C. Performance Metrics

i) *Real-time pricing policy for storage*: The price is decided on based on the real-time communication.
ii) *Utility of the customers*: Each customer tries to maximize its utility by maximizing its energy consumption, while satisfying the inequality given in (36).
iii) *Consumed energy by the customers*: The amount of energy consumed by the customers is decided on by a real-time home energy management system, and the lower limit of the consumed energy is decided on *a priori*.

D. Results and Discussions

For the sake of simulation, we assume that each microgrid calculates the real-time supply and demand in 10 s intervals. In Fig. 2(a), the comparison of consumed energy, i.e., e_n, is shown, where a_n is the same for HoMeS, E2VC, and PTU. The customer decides on the energy to be requested for storage on a real-time basis. Fig. 2(a) shows that the consumed energy in our proposed method, i.e., HoMeS, is 30% and 55% higher than that in E2VC and PTU, respectively. Using E2VC, the PHEVs consume energy for storage devices at the PHEV end, whereas using PTU, the customers are not equipped with any storage facility. On the other hand, using HoMeS, the customers can fulfill their daily energy requirement for the appliances. Additionally, using HoMeS, the customers can also utilize the storage facility at his/her end while consuming a higher amount of energy. Therefore, the energy generated by the microgrids is more adequately utilized using HoMeS than using the other approaches—E2VC and PTU.

In Fig. 2(b), the comparison of p_m is shown. p_m using E2VC is lower than using HoMeS and PTU. However, the capital earned by selling the generated energy by the microgrids is much higher using HoMeS than using other approaches, i.e., E2VC and PTU, as shown in Fig. 2(c). Using HoMeS, the supplied amount of energy is much higher than using E2VC and PTU, as shown in Fig. 2(a). Therefore, each microgrid, using HoMeS, earns more, than when using E2VC and PTU.

Fig. 3(a) shows that the percentage of excess energy, generated by the microgrids, is also lower for HoMeS than for E2VC and PTU. Therefore, Fig. 3(a) reestablishes the fact that the energy generated by the microgrids is more adequately utilized using HoMeS than using E2VC and PTU, as concluded from Fig. 2(a).

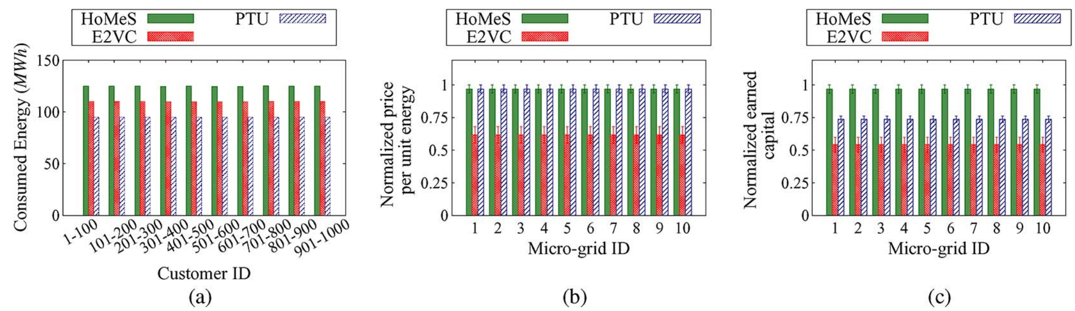

Fig. 2. (a) Energy consumption of the customers. (b) Price decided on by the microgrids. (c) Earned capital of the microgrids.

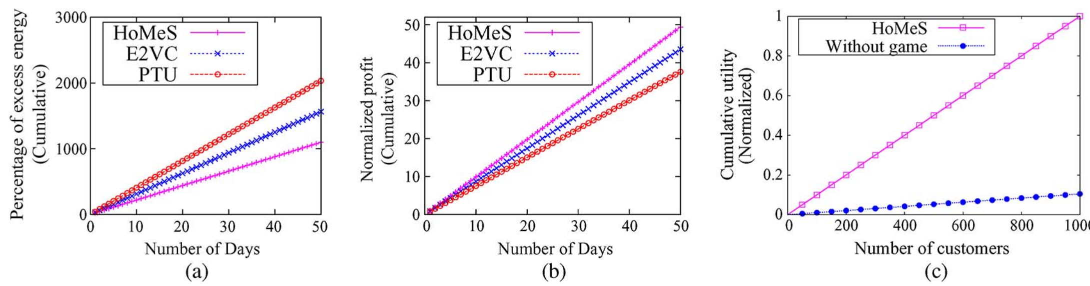

Fig. 3. (a) Excess energy. (b) Profit over days. (c) Utility of customers.

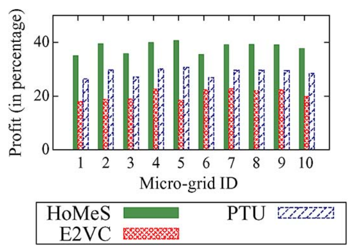

Fig. 4. Profit of microgrids.

Fig. 3(b) shows that the overall profit of the microgrids in a coalition is 15.39% and 30.79% higher using HoMeS than using E2VC and PTU, respectively. In Fig. 3(b), the cumulative profit of the microgrids is shown. On the other hand, Fig. 4 shows the profit of each microgrid, individually. Therefore, each microgrid, using HoMeS, gets a higher profit, than when using E2VC and PTU, and the overall profit of the coalition is also higher using HoMeS than when using the other approaches, i.e., E2VC and PTU. Fig. 3(c) shows that the utility of the customers, which combines the effect of utilization of energy generated by the microgrids, energy consumption of the customers with optimum price, and the profit of the microgrids, significantly varies using HoMeS, than using a different approach. Therefore, with the increase in the number of customers, the utility of the microgrids is much higher using HoMeS than when using any nongame-theoretic approach.

VI. Conclusion

In this paper, we have formulated a multiple-leader–multiple-follower Stackelberg game-theoretic approach, which is named HoMeS, to study the problem of distributed HoMeS facilities. Using the proposed approach, we showed how the distributed energy management system in the presence of storage can be done with the optimum value of the energy requested by the customers, while considering the overall energy demand in the system. On the other hand, the profit of the microgrids is also ensured, while the optimum price decided on by each microgrid is less compared with that using the traditional energy distribution mechanism. The simulation results show that the proposed approach yields improved results.

Future extension of this work includes understanding how the energy distribution can be improved by exchanging less number of messages, so that the delay in energy supply can be reduced, and the service provided by the microgrids to the customers can be improved, thereby improving the utilization of the microgrids.

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