IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received June 19, 2020, accepted July 1, 2020, date of publication July 6, 2020, date of current version July 17, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3007154

Joint Energy Management and Energy Trading in Residential Microgrid System

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This work was supported by the Deanship of Scientific Research at University of Ha'il.

ABSTRACT The sustainability of the power systems assures consumers to have efficient and cost-effective energy consumption. Consumers' energy management is one of the solutions that in fact boosts the power system stability via efficiently scheduling the appliances. In addition to energy management, consumers fulfill their low-cost energy consumption using decentralized energy generation (such as solar, wind, plug-in hybrid electric vehicles, and small diesel generator). This decentralized energy generation and its trading among the prosumers and consumers help in the distribution grid stability and continuous supply. In this paper, the joint energy management and energy trading model is presented, which provides low-cost electricity consumption to the distribution system. The proposed framework is a twofold system. In the first fold, the distribution system is divided into a number of microgrids, where each microgrid electricity demand is managed using a unified energy management approach. While the local energy produced is traded among the microgrids in the second fold, through energy trading concepts that fulfill the consumers' demand without stressing the utility company. The results indicate that the proposed model reduced the electricity cost of the microgrids with maximum share of self-generation. Moreover, the results also indicate that each microgrid either fulfills its electricity demand from self-generation or purchases it from the nearby microgrid.

INDEX TERMS Smartgrid, unified demand side management, peak to average power ratio, consumer comfort level.

NOMENCLATURE

β_1, β_2	Set of appliances having various priorities, e.g., $\beta_1 \in$ {Washing machine, dish washer} and $\beta_2 \in$ {Dryer, sterilizer}, etc.
γ^t	Peak clipping maximum limit.
$\lambda_{v,a}^{t,n}$	Consumer preference factor
A^n	Set of appliances of consumer's n.
B_v^t	Load profile of fixed or non-shiftable load.
$C(E_v^{t,g})$	Cost of energy generated by the microgrid v in time t.
$C(E_v^{t,u})$	Cost of energy purchased by the microgrid v from the utility in time t.
$C(E_{v,w}^t)$	Cost of energy purchased by the microgrid v from the microgrid w in time t.
$C(E_{w,v}^t)$	Cost of energy purchased by the microgrid w from the microgrid v in time t.
$E_v^{t,g}$	Energy generated by the microgrid v in time t.
$E_{w,v}^{t,max}$	Maximum energy purchased by the microgrid w from the microgrid v in time t.
$E_v^{t,u,max}$	Maximum energy purchased by the microgrid v from the utility in time t.
$E_v^{t,u}$	Energy purchased by the microgrid v from the utility in time t.
$E_{v,u}^t$	Energy purchased by the utility u from the microgrid v in time t.
$E_{v,v}^t$	Energy purchased by microgrid v from the microgrid v in time t, i.e., self-purchased
$E_{w,v}^t$	Energy purchased by the microgrid w from the microgrid v in time t.
$E_{w,w}^t$	Energy purchased by the microgrid w from the microgrid w in time t, i.e., self-purchased

The associate editor coordinating the review of this manuscript and approving it for publication was Salvatore Favuzza.

$H_{v,a}^{n,t}$	Human interaction factor.
L_v^t	Load shedding factor at time t in microgrid v.
$L_{v,a}^{t,n}$	Load profile of shiftable load.
N	Total number of consumers.
T	Total number of time slots.
$t_a^{s,n}$	Starting time of the a^{th} appliance of the n^{th} consumer.
t_a^n	Time taken by the a^{th} appliance of the n^{th} consumer.
V	Number of the microgrids.
$X_{v,a}^{n,t}$	Decision variable for the selection of shiftable appliances.

I. INTRODUCTION

The sharply increased demand in residential global energy market compelled the power producers to rethink the energy consumption. The depletion of conventional sources of power generation and the high cost of electricity consumption converted the consumers into prosumers. The prosumers fulfill the self energy consumption by installing their own energy generation sources like, photovoltaic (PV), wind turbine, energy storage, etc. This distributed energy generation plays an important role in curtailing the burden on the traditional power supplier companies. Australia is on the top in rooftop PV generation, about 19% of the Australia electricity generation is from rooftop PV with an expected rise to 40% by the year 2050 [1], [2].

In the literature, a number of solutions are proposed to fulfill the high rise electricity demand for residential consumers. For example, energy management algorithms are available that shift the high electricity demand of consumers into off-peak hours to reduce the overloading of the distribution system [3], [4]. The author in [5], used the concept of peer to peer energy trading to fulfill the high rise energy demand and minimizes the electricity bill by 20%. Predictive control scheme based demand response is presented by Hedegaard in [6], which not only reduces the peak hours demand but also increases the end-user saving by 46%. Similarly, rooftop renewable energy generation also helps in the fulfillment of high rise energy demand [7], [8]. The uncertainty during the fulfillment of the high rise energy demand through renewable energy generation is considered by Vahedipour in [9]. In this model, the authors used a stochastic risk-constrained framework to maximize the expected profit of the microgrid operator through the optimal scheduling of renewable resources. The authors in [10]–[12] used cost minimization as a performance metric and reduce the overloading of the power system by curtailing the peak hours demand. In [13], the author used an energy management system approach in the microgrid environment, which not only minimizes the electricity cost but also considering the consumers' satisfaction level. Similarly, a distributed generation based energy management system in the microgrid system is utilized in [14]. This framework curtail the mismatch among integrated energy system through real-time management of energy storage system. Apart from overloading the distribution system, the high electricity demand causes a number of other issues for consumers as well as for the suppliers. These issues include failure of power supply, higher cost of electricity, increase in distribution losses, higher peak hour demand, etc [15]. Energy management at the residential level is aimed to resolve these issues. The peak demand for the high rise building is reduced in [16]–[18] by using a rooftop PV and energy management algorithm. The results show that the minimization of peak demand reduces the peak to average power up to 7.32%. A hybrid power generation system along with an energy management algorithm in the microgrid environment presented in [19] reduces the electricity cost by 8.6% including maintenance cost. The authors in [20], used IoT based smart energy management system to reduce the consumers' energy consumption during peak hours. A blockchain technology-based energy management is used in [21] to minimize the higher electricity cost. The proposed framework reduced the electricity cost by 18.9%. Similarly, a game theory-based energy management algorithm is presented in [22]. The proposed model consists of a two-level game, i.e., a multi-leader-follower game between consumers and electricity supplier and a game among consumers to reduce the electricity cost and peak to average power ratio. The local energy production or co-generation uses multiple generation sources like diesel generator, power gas turbine, wind turbine, PV, etc. These co-generations provide power to needy supplier or prosumers in case of peak hours or in any demand fluctuation scenario caused by the abnormal operation of consumers [33]–[35]. The on-demand energy provision is normally termed as ''energy sharing'', ''energy exchange'', ''energy cooperation'' and ''energy trading'' which will be used interchangeably. Distributed Energy Generation (DEG) in the consumers' premises and exchange of local energy produced, plays a vital role in a sustainable power system. Sharing of DEGs minimize the short term electricity short fall normally occurring in peak hours [23], [36]. In the literature, various energy trading approaches are available that resolves consumers high energy demand [37], [38].

In [24], the authors used a robust game theory-based algorithm to maximize the payoff values for both consumers as well as for the suppliers. Similarly, the authors in [39], reduced the short term energy shortage of consumers associated with electric vehicle charging stations by introducing electric vehicle as a seller. In the proposed model, in peak hours the electric vehicle is given an option to discharge by selling the energy to the charge station at a higher price. The charge station can use that energy to fulfill the demand of other consumers. A single-leader, multiple-follower Stackelberg game based energy trading algorithm is presented in [25]. In this framework the power supplier acts as a leader while the prosumers are considered followers. Similarly, multiple-leader, multiple-follower Stackelberg game based energy trading framework is presented in [26]. Multiple distributed energy stations lead the game while the energy consumers follow the game as a result the combined benefits

TABLE 1. **Comparative analysis of literature.**

Ref.	Energy trading	Energy management	Cost minimization	Power system stability	PAPR reduction	Distribution losses reduction	Renewable generation
[11]		✓	✓	✓			
[12]		✓	✓	✓			
[10]		✓	✓				
[5]		✓	✓				✓
[8]		✓	✓				✓
[16]		✓			✓		
[18]		✓					✓
[19]		✓	✓				✓
[20]		✓			✓		✓
[21]		✓	✓				
[22]		✓	✓		✓		
[23]	✓		✓		✓		✓
[24]	✓		✓				✓
[25]	✓		✓				✓
[26]	✓		✓				✓
[27]	✓		✓	✓			✓
[28]	✓		✓	✓			
[29]	✓			✓			✓
[30]	✓		✓	✓			✓
[31]	✓		✓	✓			✓
[32]	✓		✓	✓			✓
Proposed model	✓	✓	✓	✓	✓	✓	✓

are maximized. Similarly, the authors in [27], [40]–[43], proposed game theory based energy trading approaches to minimize consumer electricity bills. A game-theoretic approach based on modified regret matching procedure is presented in [42], where the prosumers' can exchange the surplus energy with their neighbor at low price. One-leader multi-follower-type bi-level optimization model in [41] is used for the minimization of the energy cost of distribution system operators and for the maximization of the microgrid's owner profit. A reconfigurable microgrid with renewable energy resources based on optimal scheduling is used for profit maximization in [44]. In [45], the authors used distributed game theory among the various smartgrid users to maximize consumers' utility by designing a trading mechanism. A non-cooperative and non-quadratic dynamic game-based model maximizes the power system reliability by increasing the local generation and by ensuring lower market prices [27], [43]. Similarly, another non-cooperative game based energy trading mechanism between residential and commercial prosumers is discussed in [46], which minimizes the energy cost for both residential and commercial prosumers. A demand flattening management scheme in [47] is used to minimize the end-user electricity bill through a multi-agent energy trading solution. The authors in [48] proposed a vehicle to vehicle energy exchange scenario to increase the generation profit. A blockchain platform that enables peer-to-peer (P2P) energy trading the residential sector used to maximize the use of renewable energy resources which not only minimizes the energy cost but also it helps power system stability [49]. Another P2P energy trading strategy based on the energy trading price for prosumers discussed in [50]. In this model, the authors considered the electricity market of South Korea and calculate a minimum/maximum energy trading price for energy prosumers which reduces the energy cost.

The concept of energy trading to maximize the revenue of the supplier while satisfying the consumers' peak hours demand is discussed in [32], [51]. Peer to peer energy trading concept is presented in [31], [52]–[54] in order to balance the mismatch between generation and consumption. The summarized literature overview is tabulated in Table. 1.

A. MOTIVATION

From the above discussion, it is concluded that the research community has contributed a lot towards the energy management and energy trading algorithms. The shortage in short term energy is either addressed by energy management (which shifts the appliances into off-peak hours) or by employing an energy trading algorithm (which shares electricity among various prosumers and energy suppliers). To the best of our knowledge, there is no such effort where energy management and energy trading are considered jointly. Joint energy management and energy trading is still an unexplored area. To fill this gap and to efficiently manage the energy consumption with minimal electricity cost, we propose a joint energy management and energy trading solution. In the proposed research work, we incorporate the consumers' requirements (consumer's priorities, preferences and amount of budget want to spend), the importance of heterogeneous load, load profile, human interaction factor, unavailability of electricity supply, distributed generation, etc.

B. CONTRIBUTIONS

The contributions of this paper, are summed up as follows.

1) In the proposed model, we provide a joint energy management and energy trading framework, which is used to minimize the electricity cost of the power system.
2) The proposed framework considers various factors and parameters that influence the power system stability and sustainability, e.g., consumer load profile, load shedding, heterogenous load, peak clipping, valley filling, human interaction factor, appliances priority, and consumer preferences.
3) The proposed model, reduces the peak to average power ratio, perform peak clipping, flatten the energy demand curve and minimize the distribution losses.
4) The use of renewable distributed energy resources are maximized

Extensive simulations are performed to highlight and present the effectiveness of the proposed framework. Integer linear programming solver is used for the solution of the given problem.

C. PAPER ORGANIZATION

The rest of the paper is organized as follows. The mathematical model of the given joint energy management and energy trading is discussed in Section II. Simulation results are discussed in Section III. Section IV concludes the paper.

II. SYSTEM MODEL AND MATHEMATICAL MODELLING

We consider a network of microgrids shown in Fig. 1, where we have V microgrids. Each microgrid consists of N number of consumers where each consumer has a set of appliances A^n. The consumers as well as the microgrids are equipped with distributed energy generation sources like a diesel generator, PV cells, small wind turbine, etc. The consumers fulfill their energy consumption from self-generation using the mentioned resources.

All the consumers are interconnected as well as connected to the microgrid control unit. The microgrids are also interconnected through bi-directional communication and power line. In this proposed framework, there are three different scenarios.

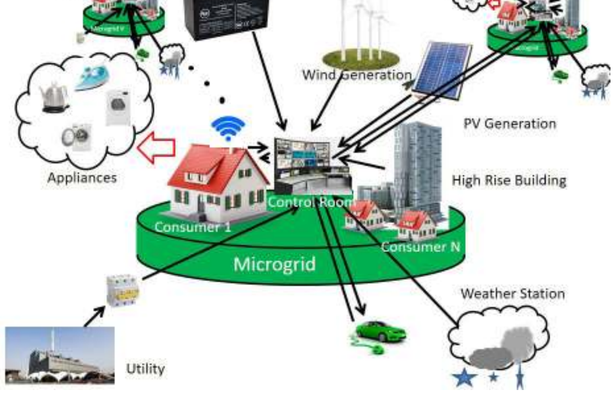

FIGURE 1. An overview of microgrid.

1) In the first scenario when the microgrid v self-generation is not enough to fulfill the local energy demand. From local energy demand, we mean the energy demand of all the consumers inside the microgrid. Then the microgrid v has to procure the energy difference from the nearby microgrid w.
2) In the second scenario if the nearby microgrid w does not have enough energy to fulfill its self demand as well as the demand of microgrid v, then it has to informed the microgrid v.
3) In the third scenario, the microgrid v will procure the difference energy from the utility company, if the self-generated power is not sufficient for the local demand.

The proposed model consists of an energy management solution followed by energy trading. Before energy trading, each microgrid reshapes its own energy consumption curve through Unified Demand Side management (DSM). The unified DSM employed at the microgrid level for the rescheduling of the shiftable load. If self-generation is insufficient to fulfill local demand, the consumer gets energy from several microgrids V, via energy trading. The given model has two modules.

- Energy management model
- Energy trading model

A. ENERGY MANAGEMENT MODEL

Each microgrid consists of N number of consumers, where each consumer has A^n set of shiftable as well as non-shiftable appliances. Some of the shiftable appliances (such as washing machine, dryer, dishwasher, etc.,) require priority for its operation. (For example, if the clothes are not washed then the operation of dryer is useless.) Therefore, such shiftable appliances are divided into groups based on their priorities. For example, washing machine and dishwasher are put in one group represented by β_1, and, sterilizer and dryer in another group β_2. That is, first the consumer will wash the clothes and then will use the dryer shown in (5). Similarly, either the sterilizer or dishwasher will be switched on at a time. To select which device to be turned on, we have a decision variable $X^{t,n}_{v,a}$ as defined in (1).

$$X^{t,n}_{v,a} = \begin{cases} 1 & \text{if the } a^{th} \text{ appliance of the } n^{th} \text{ consumer in the} \\ & \quad v \text{ microgrid is switch on at the } t^{th} \text{ time slot.} \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$H^{t,n}_{v,a} = \begin{cases} 1 & \text{if the } n^{th} \text{ consumer is available to operate the} \\ & a^{th} \text{ appliance at the } t^{th} \text{ time slot in the } v \\ & \quad \text{microgrid.} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$$L_v^t = \begin{cases} 1 & \text{if the electricity is available at the time slot } t \\ & \text{in the } v \text{ microgrid.} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

$$\lambda_{v,a}^{t,n} = \begin{cases} 1 & \text{if the } n^{th} \text{ consumer of the } v \text{ microgrid wants to} \\ & \text{operate the } a^{th} \text{ appliance at the } t^{th} \text{ time slot.} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

The decision variable has to select one of the appliances either from group β_1 or from group β_2. To mathematically model, thus, we have the following equation.

$$\sum_{a\in\beta_1} X_{v,a}^{t_1,n} + \sum_{a\in\beta_2} X_{v,a}^{t_2,n} \leqslant 1 \quad \forall\{t_1 < t_2\}, n, v \tag{5}$$

The condition $t_1 < t_2$ in equation (5) ensures that any appliance in β_1 group should be served before serving the appliances in β_2 group, where $t_1 = \{1, 2, 3 \cdots T\}$ and $t_2 = \{1, 2, 3 \cdots T\}$. Equation (5) conforms that the schedular will select a single appliance from both groups at the same time. If any of the appliances from these groups is switched on, then, the left side in the equation (5) will be "one" otherwise its value will be "zero". Further, the appliances' continuous operation should be ensured. If the number of appliances operating time slots is t_a^n, then, the value of the decision variable will be equal to t_a^n. For easy understanding, let, the washing machine operates for 30 minutes. Initially, the operation time is divided into time slots, if the slot duration is 15 minutes then the washing machine has to remain switched on for two consecutive time slots, i.e., $t_a^n = 2$. If the starting time slot for washing machine operation is $t_a^{s,n}$, then to switched on the washing machine for two-time slots the decision variable should have a value of 1, starting from $t_a^{s,n}$. In both time slots, the decision variable should have a value of 1, or we can say that the summation of the decision variable is equal to 2 for the given appliance. The mathematical representation of this constraint is given by

$$\sum_{t=t_a^{s,n}}^{t_a^{s,n}+t_a^n} X_{v,a}^{t,n} = t_a^n \quad \forall\ n, a, v \tag{6}$$

There are a number of appliances that need human existence for its operation, e.g., washing machine, electric iron, etc,. To ensure the consumers' availability for the operation of the appliance human interaction factor (HIF) needs to be considered. This factor varies from appliance to appliance. The value of HIF is either "zero" or "one" given in equation (2).

When the HIF factor is included, equation (6) become as:

$$\sum_{t=t_a^{s,n}}^{t_a^{s,n}+t_a^n} X_{v,a}^{t,n} H_{v,a}^{t,n} = t_a^n \quad \forall\ n, a, v \tag{7}$$

Some time consumer is available to operate an appliance but electricity supply is disconnected due to maintenance or some other reason. The unavailability of supply is considered as load shedding (LS) factor. The value of the LS factor is either "zero" or "one". "One" means no load shedding and "zero" mean electricity is not available represented by equation (3).

After considering the unavailability of electricity supply, equation (7) becomes as.

$$\sum_{t=t_a^{s,n}}^{t_a^{s,n}+t_a^n} X_{v,a}^{t,n} H_{v,a}^{t,n} L_v^t = t_a^n \quad \forall\ n, a, v \tag{8}$$

In addition to the mentioned constraints, one of the most important factors is the consumers' satisfaction and preferences that should not be ignored. Sometimes the unified demand-side management (DSM) schedular shifts the appliances to the time slots with reduced cost, but at that time either the consumer is unavailable or is not willing to take this opportunity. This consumer's choice is modeled as consumer preferences (CP). If the consumer has no problem with operating certain appliances then its value will be "One", otherwise its value will be "zero" given in equation (4). The mathematical representation of consumers' preferences is given by

The constraint shown in (8) will be modified after considering the CP constraint. The modified constraint is given as:

$$\sum_{t=t_a^{s,n}}^{t_a^{s,n}+t_a^n} X_{v,a}^{t,n} H_{v,a}^{t,n} L_v^t \lambda_{v,a}^{t,n} = t_a^n \quad \forall\ n, a, v \tag{9}$$

To ensure a stable power system and the continuous supply in microgrid v, the total energy demand of all consumers should not exceed the peak limit set by the microgrid administrator. To consider the peak clipping each consumer should honor these restrictions imposed by the microgrid administrator. To mathematically model this constraint, we have the following equation.

$$\sum_{t=t_a^{s,n}}^{t_a^{s,n}+t_a^n} (X_{v,a}^{t,n} H_{v,a}^{t,n} L_{v,a}^{t,n} L_v^t \lambda_{v,a}^{t,n} + B_v^t) \leq \gamma^t \quad \forall\ n, a, v \tag{10}$$

In equation (10), B_v^t is the base load of microgrid v at time t, and $L_{v,a}^{t,n}$ is the shiftable load. The constraints shown in (10) will assure minimum peak to average power ratio (PAPR). The PAPR is given by

$$PAPR = \frac{\text{peak demand of microgrid}}{\text{average demand of microgrid}} \quad \forall\ v, t \tag{11}$$

In equation (11), if the value of the nominator is reduced then PAPR will also be reduced. Moreover, while limiting the peak demand, the line losses will be also reduced. DSM schedular has to reshape the consumers' energy consumption curve through the shifting of appliances under the mentioned constraints. As shown in Fig. 1, each microgrid has a certain amount of self-generation. The consumers' energy demand will be fulfilled by utilizing the microgrid's self-generation. If demand exceeds the self-generation capacity then the surplus generation of the nearby microgrid would be utilized.

If the neighboring microgrid does not have surplus energy, then the demanded load will be fulfilled from the utility.

Each microgrid has energy cost consisting of different sources, i.e., self-generation procured energy from neighbor microgrid/utility, and the surplus energy sold out to other microgrids and utilities. The DSM model has to reschedule the energy consumption of all the consumers inside the microgrid, such that the cost of electricity consumption is reduced.

B. ENERGY TRADING MODEL

The microgrids network is shown in Fig. 1 has multiple generation resources, e.g., PV cell, small wind turbine, and utility. Moreover, the figure also shows that each microgrid is connected to the neighboring microgrids, where they can exchange energy based on their electricity demand. Each of the mentioned sources has its own cost per unit energy production. The per-unit production cost of self-generation is normally low, while the energy procured from neighboring microgrids costs higher. Similarly, the cost of electricity purchased from the utility will be too high.

The microgrid v has to fulfill the local energy demand of all the consumers from three sources. First of all, the total rescheduled energy demand will be fulfilled from local energy production, i.e., $E_v^{t,g}$. Where $E_v^{t,g}$ represent the generated energy by the v microgrid in the t^{th} time slot. If the rescheduled demand is more than local energy produced, the microgrid v has to procure energy from other sources, i.e., neighboring microgrid or from the utility. The mathematical form of the procured energy is represented by $E_{v,w}^t$ and $E_v^{t,u}$. Where $E_{v,w}^t$ is the energy procured by the v microgrid from the w microgrid at the t^{th} time slot. Similarly, the $E_v^{t,u}$ is the amount of energy procured by the v microgrid from the utility at the t^{th} time slot. Moreover, if the rescheduled energy demand is less than the local energy generated, then, the microgrid v has to sell the surplus energy to the nearby microgrid w or to the utility company under the net sale/purchase agreement.

There should be some limitations for each microgrid. The microgrid v either sale or purchase the excess/difference energy at a time, the mathematical model of this limitation is given by

$$E_{v,w}^t \times E_{w,v}^t = 0 \quad \forall \ t, v, w \tag{12}$$

Equation (12) represents that at time t either the v microgrid will sell the surplus energy to the microgrid w or procure the needed energy from the microgrid w. At the same time, both selling and purchase will not be allowed.

Another constraint is the self sale/purchase, i.e., no microgrid can sell or purchase from itself. The mathematical representation of self sale/purchase constraints is given by

$$E_{v,v}^t = 0 \quad \forall \ v, t \tag{13}$$

To maintain the power system stability, each microgrid has a limitation over the purchase energy either from the neighboring microgrid or from the utility. To ensure the sustainability of the power system. These constraints are mathematically model as

$$0 \leq E_{v,w}^t \leq E_{v,w}^{t,max} \quad \forall \ v, w, t \tag{14}$$

$$0 \leq E_v^{t,u} \leq E_v^{t,u,max} \quad \forall \ v, t \tag{15}$$

In (14), the $E_{v,w}^{t,max}$ is the maximum limit of the purchase energy from the microgrid w, while $E_v^{t,u,max}$ in (15) is the maximum limit of purchased electricity from the utility. Similarly, there should be an upper bound on the electricity generation for each microgrid. The upper bound on self-generation is given by

$$0 \leq E_v^{t,g} \leq E_v^{t,g,max} \quad \forall \ v, t \tag{16}$$

The total energy generated and procured from all the neighboring microgrids as well as from the utility should be equal to the total energy demand and the total energy sold out. This load balancing is mathematically modeled in equation (17).

$$E_v^{t,u} + E_v^{t,g} + \sum_{w=1}^{V} E_{w,v}^t = \sum_{w=1}^{V} E_{v,w}^t + E_{v,u}^t + B_v^t + \sum_{a \in A^n} X_{v,a}^{t,n} L_{v,a}^{t,n} \tag{17}$$

In (17), the total energy generated by the microgrid v, purchased from utility and from the others microgrids is equal to the summation of baseload, i.e., B_v^t, shiftable load, i.e., $L_{v,a}^{t,n}$ and the total energy sold out to the other microgrids and to the utility.

The total electricity cost is the combination of energy purchased from utility $C(E_v^{t,u})$, cost of self-generation $C(E_v^{t,g})$, cost of energy purchased from other microgrid $C(E_{w,v}^t)$ and revenue collected by selling the surplus energy to other microgrids $C(E_{v,w}^t)$ and to the utility $C(E_{v,u}^t)$. In general, the total cost of energy is given by

$$\sum_{t=1}^{T} \sum_{v=1}^{V} \Big(C\left(E_v^{t,u}\right) + C\left(E_v^{t,g}\right) - C\left(E_{v,u}^t\right) + \sum_{w=1}^{V} \left(C\left(E_{w,v}^t\right) - C\left(E_{v,w}^t\right) \right) \Big) \tag{18}$$

The objective of our proposed framework is to reduce the energy cost of all microgrids while satisfying all the associated constraints. The overall mathematical modeling of the proposed framework is summarized in equation (19), as shown at the bottom of the next page.

III. SIMULATIONS AND RESULTS

To show the effectiveness of the proposed model, extensive simulations were carried. In this Section, V microgrid with N number of consumers having two sets of appliances, i.e., shiftable and non-shiftable are considered. Every microgrid has its own self-generation in the form of solar, wind, etc. Besides the self-generation, each microgrid is connected with other microgrids in order to trade the surplus energy.

Moreover, all the microgrids are also connected to the utility via a two-way communication link. Two-way communication links enabled the microgrid to sell/purchase the required or surplus energy.

In the proposed framework, the energy demand of each microgrid is shared with the energy scheduler module installed inside that microgrid. As the scheduler can reshape the energy consumption curve by shifting the shiftable appliances under the given constraints. This rescheduled energy demand is shared with the energy trading center. The trading center calculates whether the microgrid v is self-sufficient in energy production or needs to purchase the extra required energy from other sources. Similarly, the trading center also calculates the surplus energy that the microgrid v can exchange or trade. The overall framework is presented in Fig. 2.

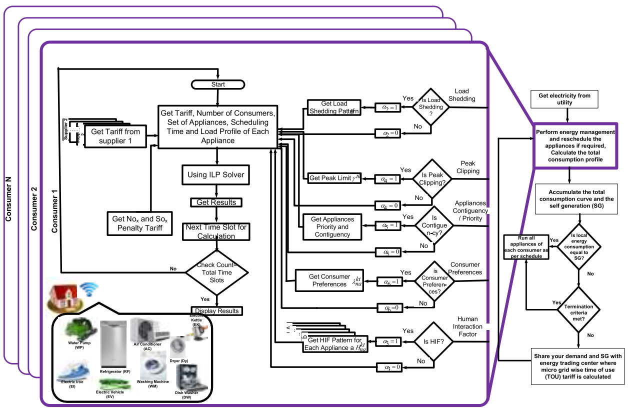

FIGURE 2. Proposed flow chart.

In Fig. 2, initially all the microgrids get electricity supply from the utility. The energy scheduler installed inside each microgrid has to calculate the total energy consumption of each microgrid. After collecting the data regarding energy consumption, the scheduler performs appliance rescheduling. The proposed approach in the flow chart takes a number of inputs including, energy pricing tariff, i.e., TOU, number of consumers, type of loads, set of appliances, power profile of each appliance, and the associated constraints. The constraints including load shedding, peak clipping, appliances continuous operation, consumer preferences, and human interaction factor. After collecting these inputs, the integer linear programming solver is used to minimize the cost of electricity by scheduling the given set of appliances. The rescheduled energy demand along with the amount of self-generated energy is then shared with the trading center. The trading center calculates an updated TOU tariff for each microgrid, which is sent back to each microgrid. Each microgrid energy management module reshapes the energy consumption according to the new tariff calculated by the trading center and shares its energy consumption curve with the trading center. This process continues until the total cost of energy consumption is minimized.

A. CASE STUDIES

In this sub-section, we randomly pick washing machines, dryers, dishwashers, and electric vehicles from different consumers of each microgrid. The energy management module is provided with various inputs like power profile, availability of consumers, preference and priorities of consumers, human interaction factor, load shedding factor, and TOU tariff from utility side, etc. The energy consumption curve of

$$
\begin{aligned}
&\min_{X_{v,a}^{t,n}\in\{0,1\}\ \forall\ v,n,t,a} \sum_{t=1}^{T}\sum_{v=1}^{V}\left(C\left(E_v^{t,u}\right)+C\left(E_v^{t,g}\right)-C\left(E_{v,u}^{t}\right)+\sum_{w=1}^{V}\left(C\left(E_{w,v}^{t}\right)-C\left(E_{v,w}^{t}\right)\right)\right)\\
&S.t \qquad C1: E_v^{t,u}+E_v^{t,g}+\sum_{w=1}^{V}E_{w,v}^{t}=\sum_{w=1}^{V}E_{v,w}^{t}+E_{v,u}^{t}+B_v^t+\sum_{a\in A^n}X_{v,a}^{t,n}L_{v,a}^{t,n}\quad \forall\ v,w,n,t\\
&\qquad\quad C2: \sum_{t=t_a^{s,n}}^{t_a^{s,n}+t_a^n} X_{v,a}^{t,n}H_{v,a}^{t,n}L_v^t\lambda_{v,a}^{t,n}=t_a^n\quad \forall\ n,a,v\\
&\qquad\quad C3: \sum_{t=t_a^{s,n}}^{t_a^{s,n}+t_a^n}(X_{v,a}^{t,n}H_{v,a}^{t,n}L_{v,a}^{t,n}L_v^t\lambda_{v,a}^{t,n}+B_v^t)\leq\gamma^t\quad \forall\ n,a,v\\
&\qquad\quad C4: \sum_{a\in\beta_1}X_{v,a}^{t_1,n}+\sum_{a\in\beta_2}X_{v,a}^{t_2,n}\leqslant 1\quad \forall\ \{t_1<t_2\},n,v\\
&\qquad\quad C5: E_{v,v}^t=0\quad \forall\ v,t\\
&\qquad\quad C6: E_{v,w}^t\times E_{w,v}^t=0\quad \forall\ t,v,w\\
&\qquad\quad C7: 0\leq E_{w,v}^t\leq E_{w,v}^{t,max}\quad \forall\, v,w,t\\
&\qquad\quad C8: 0\leq E_v^{t,u}\leq E_v^{t,u,max}\quad \forall\ v,t\\
&\qquad\quad C9: 0\leq E_v^{t,g}\leq E_v^{t,g,max}\quad \forall\, v,t
\end{aligned}\tag{19}
$$

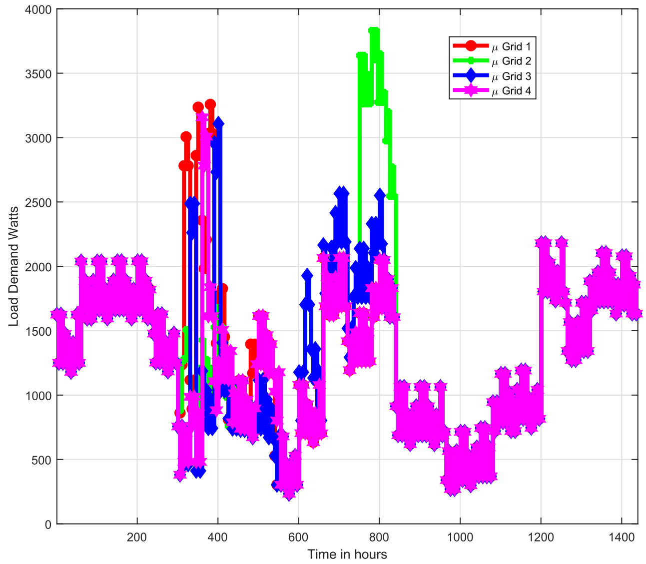

FIGURE 3. **Energy consumption curve of various microgrid without energy management and energy trading.**

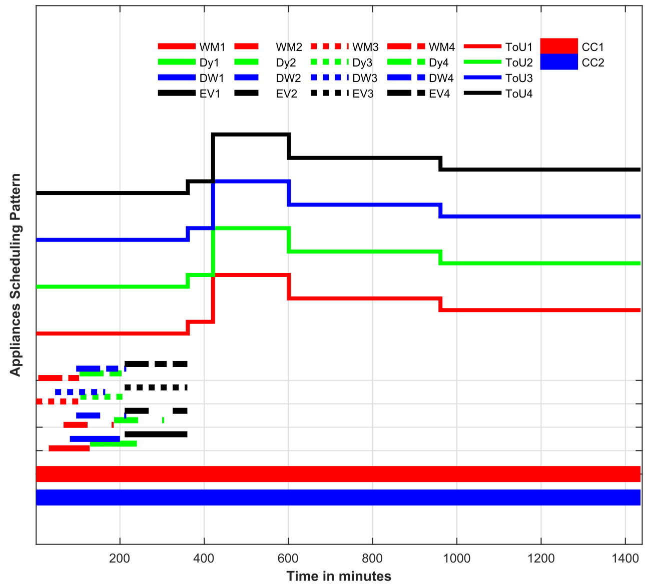

FIGURE 4. **Appliance position without any constraint and energy trading.**

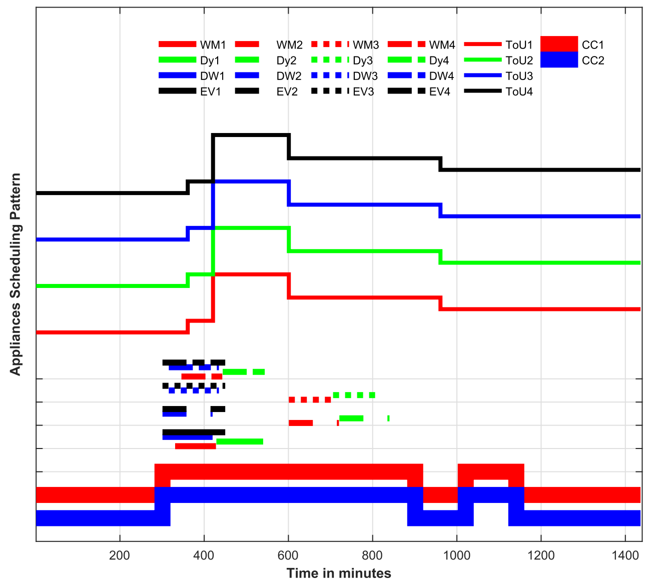

FIGURE 5. **Appliances placement after DSM without energy trading.**

each microgrid is shown in Fig. 3. In this figure, the energy consumption curve consists of shiftable as well as baseload. Normally, 40 to 50% of the total household appliances are considered to be shiftable appliances. The proposed model will be applicable to the shiftable appliances only. Throughout the paper, all the simulations were conducted for 24 hours which is divided into 1440 minutes.

Case 1:

As discussed in the first paragraph, of Section III, the scheduler were provided with appliances profile and TOU tariff from the utility. The scheduler applied energy management with no constraint and rescheduled the appliances in the time intervals where the cost of electricity is low, as shown in Fig. 4. The y-axis of the figure represents the appliance's scheduling pattern, while the x-axis represents the time. In this figure, the appliances are scheduled in those time slots where the cost of electricity is low, i.e., from 80-350 minutes on the x-axis. Moreover, there is no constraint imposed, since the appliances schedule is according to the TOU tariff provided from the utility.

Case 2:

Based on the information collected, the energy management scheduler performed appliances rescheduling under the given constraints, shown in Fig. 5. In this figure,all the appliances of each microgrid are shifted to the time interval, i.e., 950-1250 minutes where the price per kWh is low and all the associated constraints are met. Although the lowest price per kWh is in the time interval 0-360 minutes as the cumulative constraints (CC) are not satisfied from 0-400 minutes, therefore, the appliances are rescheduled between 950-1250 minutes interval. The HIF, LS, and CP constraints for washing machine (WM), dishwasher (DW), and dryer (Dy) are simulated as one cumulative constraint represented by "CC1 constraint" in the same figure. While HIF, LS, and CP constraints for electric vehicle (EV) are represented by "CC2 constraint".

Case 3:

Once the appliances rescheduling is completed, the energy management scheduler of each microgrid shares the power consumption curve as well as the amount of self-generated power as shown in Fig. 6, with the energy trading center. The energy trading center calculates microgrid wise updated TOU tariff (based on 5 minutes time slot) and shares it with each microgrid as shown in Fig. 7. In this figure, each microgrid has a different TOU tariff because the self-generation of each microgrid is different. Based on the updated TOU tariff of each microgrid, the energy management scheduler shift the

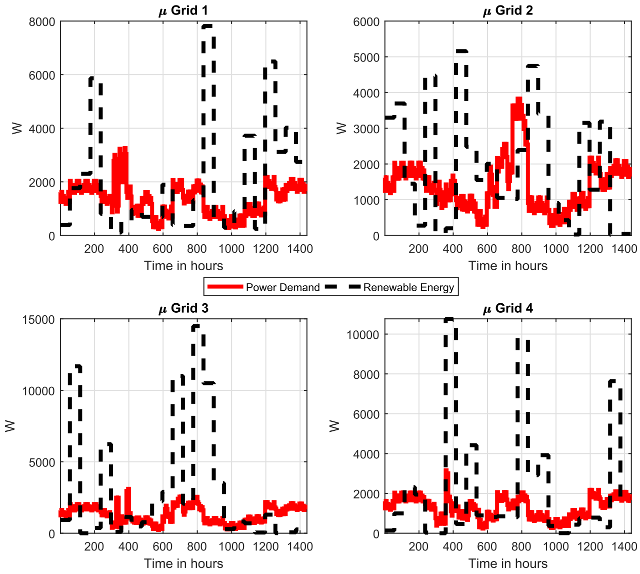

FIGURE 6. Microgrid wise self-generation and consumption curve.

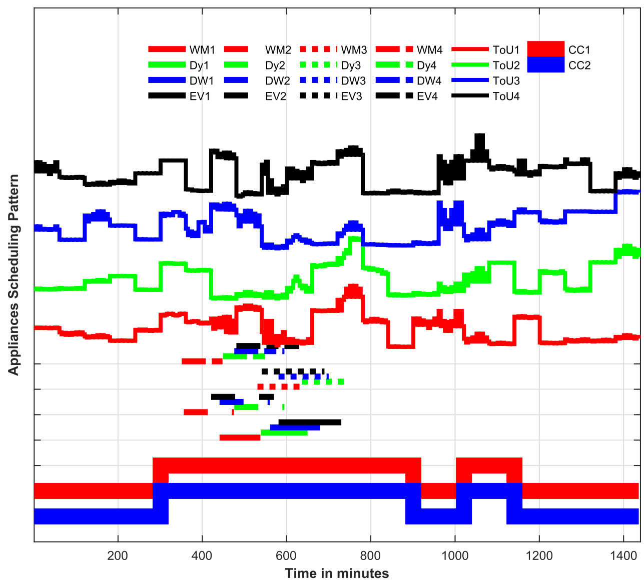

FIGURE 7. Microgrid based time of use tariff.

position of the shiftable appliance of each microgrid accordingly as shown in the same figure.

For example, the appliances of microgrid # 1 are shifted to the time interval 1080-1370 minutes, where the per kWh cost of the microgrid # 1 is lower as well as the constraints are also not violated. Similarly, the micro grid # 2 appliances are shifted to 420-580 minutes, as the per kWh cost of microgrid # 2 is lower in this interval and the same is the case in microgrid # 3 and # 4, respectively.

The microgrid, where the self-generation is not sufficient for the local demand, will purchase electricity from the nearby microgrids via an updated TOU tariff. Similarly, the microgrid's where the local energy demand is less than self-generation, sell the surplus energy to the needy microgrid. The amount of energy sale/ purchase by each microgrid is shown in Fig. 8. In this figure, we can see that the microgrid which has surplus energy can sell energy to the other microgrids. If none of the microgrids is available to purchase the surplus energy then the microgrid sell it to the utility. Similarly, in the case where the microgrid's self-generation does not meet the local energy demand then it will procure energy from the microgrid, which offers the lowest cost. If there is no microgrid with surplus energy then it will procure it from the utility. The energy consumption curve of each microgrid is modified and shared with the energy trading center accordingly as shown in Fig. 9.

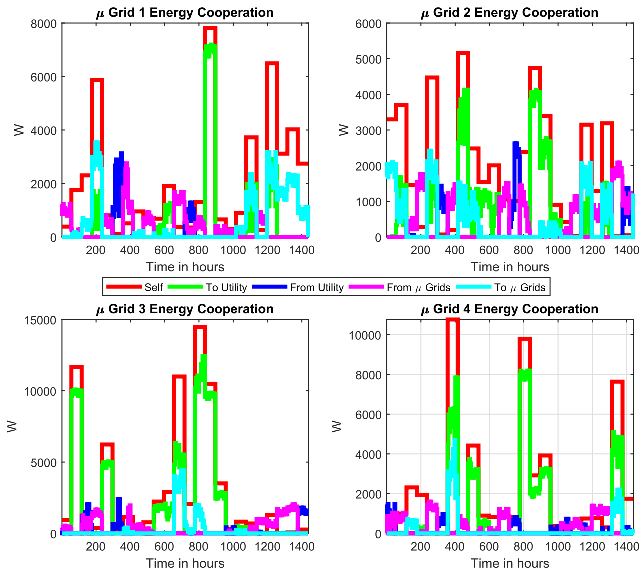

FIGURE 8. Energy cooperation among the microgrids.

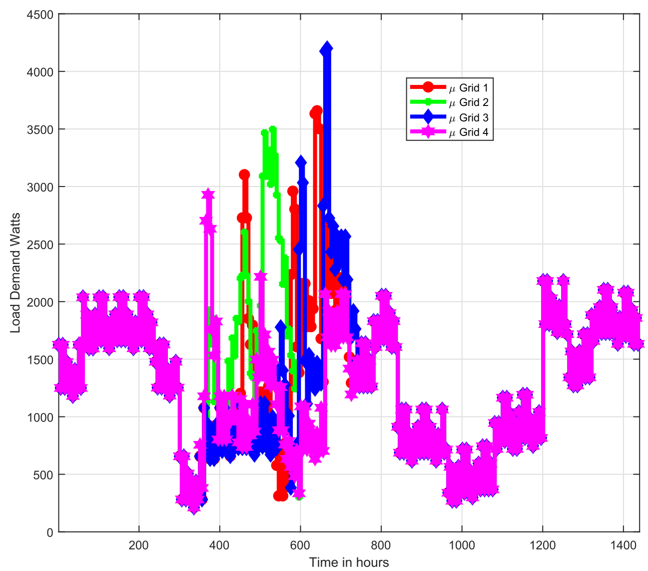

FIGURE 9. Energy consumption curve of various microgrid after energy cooperation/trading.

The local energy consumption curve changes according to the tariff of each microgrid. The consumption versus self renewable generation curve changed as shown in Fig. 10.

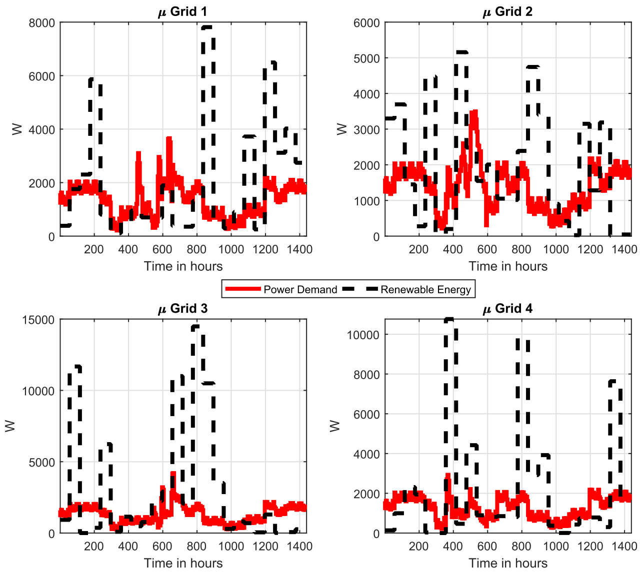

FIGURE 10. Microgrid wise self-generationand consumption curve.

Case 4:

The energy management scheduler of each microgrid sends the updated energy consumption curve and the amount of self-generated power to the energy trading center. Where the corresponding TOU tariff is calculated and shared among the microgrids. The energy management module has to perform rescheduling based on the modified TOU of each microgrid. The modified TOU tariff and the appliances rescheduling of each microgrid is shown in Fig. 11.

The modified TOU tariff of each microgrid is shared with other microgrids. The energy trading as shown in Fig. 12 is

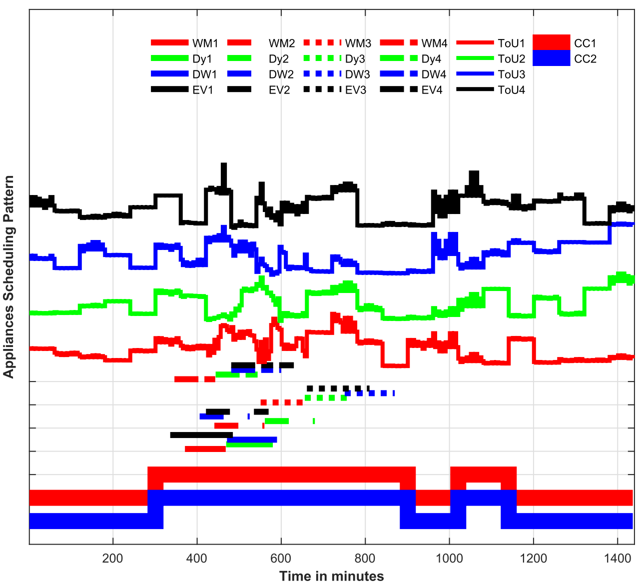

FIGURE 11. Microgrid based time of use tariff and appliances rescheduling.

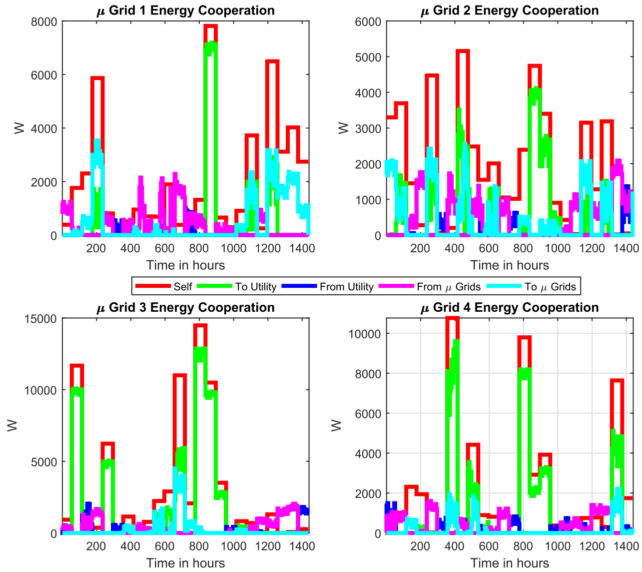

FIGURE 12. Energy cooperation among the microgrids based on updated TOU.

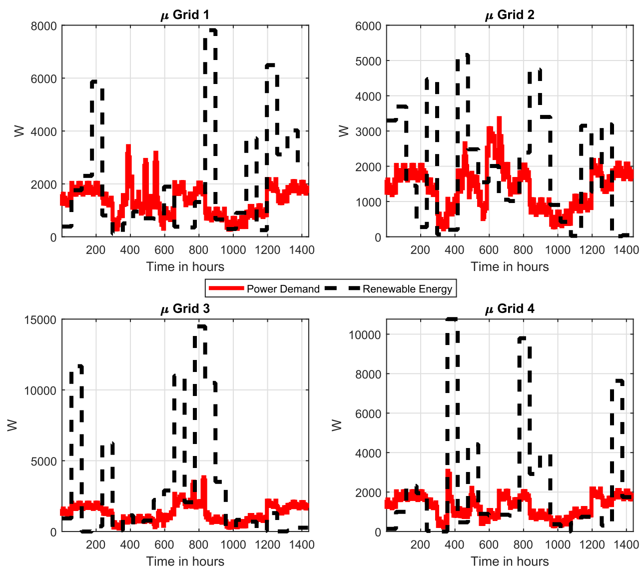

FIGURE 13. Microgrid wise self-generationand updated consumption curve.

performed based on the updated TOU tariff of each microgrid. In this figure, we can see that the energy procured from the utility by each microgrid is less than the energy procured by the same microgrids earlier, shown in Fig. 8. Moreover, in this figure, it is shown that the demand curve of each microgrid is somehow equal to self-generation. From this figure, it can also be said that the consumers are encouraged to use self-generation (distributed generation).

As the position of appliances changed according to the new tariff as shown in Fig. 11, the self-generation versus demand curve of each microgrid will also be updated. The updated demand curve versus the self-generation curve of each microgrid from the utility is shown in Fig. 13. From this figure, we can see that the scheduler rescheduled all the shiftable appliances to the time interval where the cost is

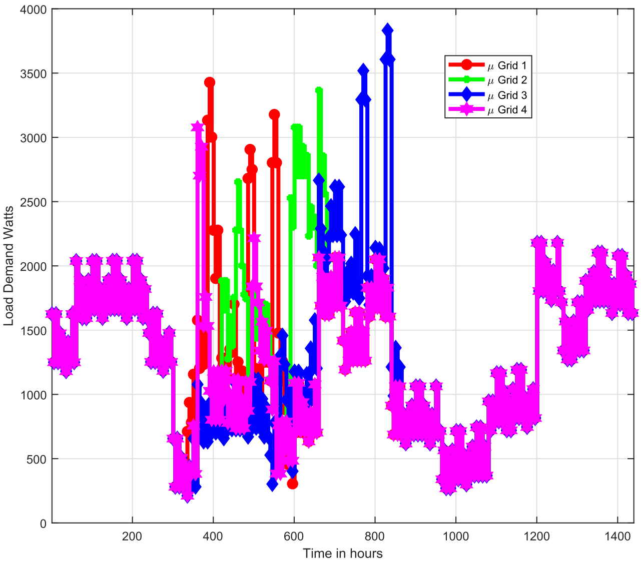

FIGURE 14. Energy consumption curve of various microgrid after energy trading.

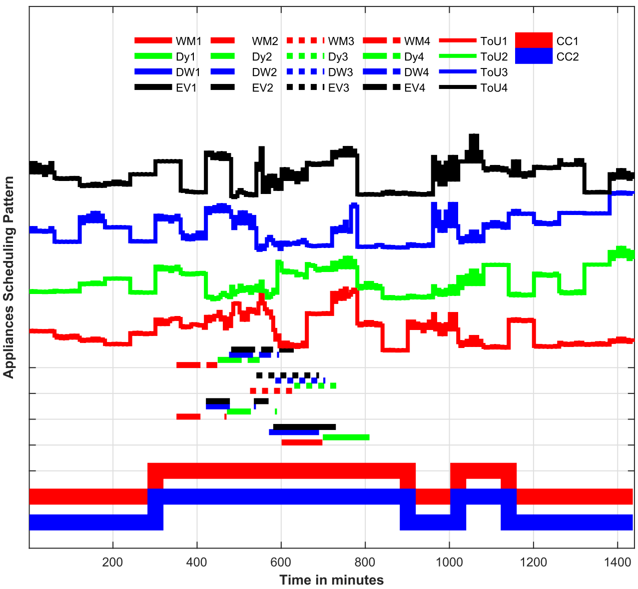

FIGURE 15. Microgrid based time of use tariff and appliances rescheduling.

low as well as the constraints are met. From the same figure, we can visualize that the scheduler shifts the position of the appliances to the time interval where the self-generation is maximum. In the same way, the maximal use of renewable energy generation is encouraged

The updated demand curve of each microgrid (shiftable and baseload) is shown in Fig. 14.

Case 5:

Now the energy scheduler will again send the updated demand curve and the self-generation curve to the energy trading center, where the TOU is updated and share with all microgrids. This procedure will continue until the termination criteria. The termination criteria may the number of iteration, objective attainment, etc. In our case, we have put the objective attainment as the termination criteria. The appliances rescheduling and the energy exchange will continue until the cost is minimized.

The final results extracted from the proposed framework show that the overall cost of energy is reduced via energy cooperation followed by energy management. The microgrid wise TOU tariff as shown in Fig. 15 is the best possible tariff where all the constraints are meeting and the overall cost of each microgrid is reduced. Moreover, the tariff as shown in Fig. 15 also encourages the other microgrids to switch their shiftable load to the time interval where the electricity cost is minimal. This redistribution of demand curve minimizes the peak demand of each microgrid which helps to curtail the PAPR. This peak clipping not only reduces the distribution losses but also plays an important role in PAPR reduction shown in equation (11).

IV. CONCLUSION

In this work, we have presented a mathematical model for joint energy management and energy trading. The proposed framework considered multiple microgrids where each microgrid has multiple consumers. The microgrid is provided with a number of inputs including set of appliances, power profile of each appliance, type of appliances, utility tariff, self-generation tariff, human interaction factor, load shedding factor, consumer's preferences, and priorities, etc. On the basis of these inputs, the energy management scheduler shifts the appliance position and shares the demanded curve with the energy trading center. In addition to the demanded curve, each microgrid also shares the self-production with energy trading center. Based on the demanded curve and self-generation of each microgrid, the energy trading center calculates the TOU tariff for all microgrids, simultaneously. The energy trading among the microgrids was performed on the basis of TOU calculated. Simulation results considered a set of random shiftable appliances from various consumers inside the microgrid. Initially, each microgrid was fed electricity from the utility where the cost per kWh is higher. Once the scheduler performs rescheduling, each microgrid is provided two options, i.e., either to procure energy from the other microgrids or sell the surplus energy to other microgrids or to the utility. The per kWh cost of purchasing electricity from other microgrids is lower than the utility as the in-house self-generation is renewable. In case the connected microgrids do not fulfill the energy demand of a microgrid then that microgrid has to purchase electricity from the utility. Simulation results showed that most of the energy consumption of each microgrid is either fulfilled from the self-generation or from the neighboring microgrids. In future work, we will work on the computational complexity reduction and ramp constraint consideration.

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