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A Novel Approach to Neighborhood Fair Energy Trading in a Distribution Network of Multiple Microgrid Clusters

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***Abstract*—The microgrids (MGs) have emerged as an ideal platform to integrate distributed energy resources (DER'S) in a distribution network. However, the intermittent nature of DER's poses a new challenge of energy balance within a microgrid. Trading energy among the microgrids has emerged as a well-suited solution. Therefore, we have proposed a novel method for fair and stable energy sharing among microgrid clusters with minimum information overhead. The novelty of the proposed method lies within the seller level game and introduction of a new pricing mechanism. The concept of an aggregator is used as a mediator between the trading parties. Depending on the priority factor, each buyer MG decides its strategy for energy demand from the surplus using a non-cooperative game theory based algorithm. The interests of seller MGs are protected by allowing them to decide the amount of energy they want to share out of their total surplus. To avoid the selfish behaviour of any buyer MG, an algorithm is used by the energy market operator which verifies the strategies submitted by buyer MGs before releasing set points to the generators. Apart from fairness and stability, the extensive numerical study confirms the ascendancy of the proposed method.**

***Index Terms*—Distributed energy resources (DER's), energy trading, game theory, microgrids, multiple microgrid clusters.**

ACRONYMS

BAA	Buyer Aggregator Agent
DERs	Distributed Energy Resources
DG	Distributed Generation
EMO	Energy Market Operator
FGA	Field Generation Agent
LA	Load Agent
FLA	Field Load Agent
GA	Generation Agent
GT	Game Theory
MAS	Multi Agent System
MEMA	Microgrid Energy Management Agent
MG	Microgrid
NE	Nash Equilibrium
SAA	Seller Aggregator Agent

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NOMENCLATURE

$\mathcal{N}$	Set of N MGs in a distributed network
G_i	Energy generated during given fixed time interval
L_i^{min}	Essential load demand of ith MG
P	Index set of all seller MGs
L_i	Updated energy consumption by ith seller MG
Q	Index set of all buyer MGs
$E_{ex,i}$	Excess energy available with ith seller MG
$E_{ex,i}^*$	Excess energy available with ith seller MG after adjusting its load consumption
$E_{req,i}$	Energy requirement of ith buyer MG
E_{req}	Total energy requirement of all buyer MGs
E_{extra}	Total excess energy available from all seller MGs before adjusting their load consumption
E_{extra}^*	Total excess energy available from all seller MGs after upgrading their individual load demand
ρ	Per unit cost of energy decided by BAA
G_{sp}	Grid selling price
G_{bp}	Grid buying price
EA_i	Energy Allocated to ith buyer MG
d_i	Strategy of ith buyer MG
z_i	Preference parameter of ith seller MG
γ_i	Priority Factor of ith buyer MG
μ	A weight factor
C_{BAA}	Total cost incurred to the BAA for buying energy on behalf of all buyer MGs
C_i	The number of contributions recorded by ith buyer MG till present interval
D_i	The load demand of ith buyer MG in the present interval
C_{Total}	The total number of contributions recorded by EMO till present interval
D_{Total}	Load demand of all buyer MGs in the present interval
ϑ	A small positive value
h	Energy height

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I. INTRODUCTION

THE penetration of distributed generation (DG) at distribution network level is increasing in almost all countries worldwide. The distributed energy resources (DERs) basically consist of solar photovoltaic (PV) modules, small wind turbines (WTs), electricity storage and controllable loads. The carbon emission-less operation along with free and ample availability makes these technologies more relevant and popular in modern days, especially under current energy scenario. These technologies are expected to play a significant role in the future electricity supply [1]. Since DERs are located in close vicinity of the loads, the power quality and reliability of electricity supplied by them will improve substantially [2]-[4]. The integration of DERs in the distribution network will further reduce the line losses and the need for rapid grid expansion. A microgrid has emerged as an ideal platform for integrating DERs in a local distribution network [3] [4]. However, controlling a large number of DERs creates a huge challenge for operating and controlling the microgrid safely and efficiently especially if non-dispatchable DERs such as PV or wind are involved [1]. Due to the presence of non-dispatchable DERs, there always exists a problem of demand-supply mismatch in a microgrid. One possible solution to tackle this problem is to install diesel generators or to use large scale centralized storage devices. However, emissions due to diesel and operating cost of storage devices are much higher than DERs, therefore, it is ideal to look for an alternative smart mechanism to deal with the energy imbalance problem faced by the microgrids [5].

Several recent papers investigates energy management in the multi-microgrid clusters include [6]-[22] and the references therein. The autonomous microgrids with the independent operator can exchange energy among themselves rather than trading with the main grid. This operating scenario creates a new energy market in a distributed network with multiple microgrids. Thus, there is a need to design a computational framework and control strategies for smart microgrids to facilitate energy trading among them.

A. Related Work

Due to inherent characteristics such as reactivity, pro-activeness and social ability, multi-agent-systems (MAS) are used in power engineering applications especially in multi-microgrid systems [5]-[7]. The fundamental concepts and approaches related to the multi-agent systems that are appropriate to power engineering applications are discussed in [23] along with a comprehensive review of the applications for which MAS are being investigated. The guidance and recommendations on how MAS can be designed and implemented is given in [24]. Kumar Nunna *et al*. [6] used a MAS based two - level architecture for DER's management in intelligent microgrids. In the proposed mechanism buyers and sellers are matched using a naïve auction algorithm. This mechanism works only if there are an equal number of buyer and seller MGs present in the market. Another drawback is that it requires a centralized auctioneer. T. Logenthiran *et al*. in [7] proposed a three - stage algorithm which assumes that each microgrid and lumped load has market price forecasting capability and they bid at their forecasted market prices. However, an accurately forecasted market price is required for each player to ensure success in the energy market.

TABLE I
COMPARISON OF VARIOUS GT BASED ENERGY TRADING METHODS

Aspects	Methods					
	SLMF	MLMF	CB	PI	Baseline	Proposed
Seller level game	Yes	Yes	No	No	No	Yes
Buyer level game	Yes	Yes	Yes	Yes	No	Yes
Priority of buyers	No	No	Yes	Yes	No	Yes
Distributed at local level	Yes	Yes	Yes	Yes	No	Yes
Pricing	Yes	Yes	No	No	Yes	Yes
Existence of NE	Yes	Yes	Yes	Yes	No	Yes
Elimination of selfish behaviour	No	No	Yes	Yes	No	Yes

SLMF: Single leader multi followers [15], MLMF: Multi-leader multi-follower [17], CB: Contribution based [18], PI: Priority index based [19], Baseline: Trading with the main grid.

Several game theoretical strategies were also proposed in [8]-[22] for energy management in a network of multiple MGs. Each microgrid needs to decide its local strategy on how to maintain local supply/demand balance as well as market strategy on how to interact with the neighboring microgrids. Under such circumstances, game theory found suitable to model and design strategies for energy trading among smart Microgrids [5]. A cooperative power dispatching in interconnected microgrids is presented in [8] by Mohammad Fathi *et al*. and incorporated impact of demand uncertainty in [9]. In [8] and [9] authors considered that the microgrids are controlled by a centralized operator which may not be a case always. The microgrids can operate as autonomous entities as well. The study in [10] has considered a hierarchical structure for interactions between the main grid and the cluster of microgrids. The direct energy trading among microgrids is explored in [11] and [12]. Matamoros *et al.* [11] proposed an energy trading mechanism for islanded MGs and D. Gregoratti *et al*. [12] have proposed a distributed convex optimization framework for energy trading between islanded microgrids without giving any due consideration to the self-interests of multiple MGs.

In recent work, Hao Wang *et al.* [13] suggested an incentive mechanism using Nash bargaining theory to encourage proactive energy trading and fair benefit sharing among microgrids. W. Saad *et al.* used the coalitional game theory in [14] for energy scheduling among multiple microgrids with the goal of minimizing average power loss in the distribution network. However, this mechanism suffers from the problem of large communication overhead. Also, the issues of fairness as well as proactive participation of microgrids are not addressed. Leader-follower strategies for energy management of multi-microgrids are proposed in [15]-[17]. W. Tushar *et al*. [15] suggested a non-cooperative Stackelberg game between the residential units and the shared facility controller in order to explore how both entities can benefit from their energy trading with each other and the grid. Asimakopoulou *et al*. [16] and J. Lee *et al.* [17] have presented interactions between the main grid and microgrids in hierarchical order. However in

[17], since all buyers are bidding the same value at NE, proactive participation especially from buyer MGs is not ensured. This is because, the excess energy is distributed among the buyer MGs proportional to their bid placed.

Sangdon Park *et al.* [18] have designed a contribution-based energy-trading mechanism among MGs in a competitive market. However, calculation of contribution factor is not defined. This is a non-pricing based approach. This work is extended in [19] by suggesting a priority index for buyer MGs based on past contributions and local load demand. In [18] and [19], authors have designed strategies only for buyer MGs without giving any due consideration to the interests of seller MGs. Also, non-inclusion of pricing makes these studies practically less attractive. For real time implementation of any trading mechanism, a suitable pricing need to be incorporated. A brief comparison of various game theory based energy trading methods reported in the literature and close to our proposed work is presented in table I.

B. Our Contribution

This paper presents a novel approach to overcome the shortcomings of the existing work reported in [17], [18] & [19]. In the proposed method, we have designed a seller level game to protect the interests of seller MGs. We have also introduced a simple pricing mechanism to avoid complex bidding algorithms. This makes proposed method practically more relevant. It is clear from table I that the proposed method overcomes the limitations of previously reported work and qualifies in all aspects considered.

Unlike the most reported work, the computational framework designed for energy management in a multi-microgrid system should consider the priority of its members while sharing energy. The self-interests of individual microgrids should be protected and fairness must be ensured as each microgrid is a rational player. In order to sustain energy trading, an efficient incentive mechanism must be in place to encourage proactive energy trading among microgrids rather than trading with the main grid. Keeping all this in mind, we have designed strategies for both buyer and seller MGs. The suggested novel pricing mechanism also reduces the burden of large communication overhead.

The microgrids with deficiency of energy register themselves as buyers at BAA. BAA is an aggregator working on behalf of the cluster of buyer microgrids. Based on energy requirements of buyers, grid buying, and grid selling prices, the BAA decides the optimal bid value for energy purchase from the neighborhood cluster of seller MGs. Looking at the bid placed by BAA, MGs with surplus energy chooses its strategy i.e. adjusts its own energy consumption and makes remaining energy available for sell. SAA will then aggregate this available energy for sell and informs the BAA. BAA forwards this information to all buyer MGs. Based on the priority factor, each buyer MG calculates its strategy for buying energy from available surplus and submits it to Energy Market Operator (EMO). The EMO will then verify the strategy submitted and will allocate the same amount of energy to the buyer MGs who follows NE and it is proportional to their priority factor. This mechanism ensures stable operation of the proposed system and protects interests of both the seller as well as buyer MGs.

The main contributions of this work are summarized as below:

- *Inclusion of strategies for seller and buyer MGs:* Unlike the reported work in the literature as shown in table I, we have designed strategies for both seller as well as buyer MGs keeping in mind their individual interests to trade energy among themselves rather than trading with the main grid. A priority factor is being calculated for each buyer MG which helps in prioritizing the buyers while sharing excess energy from neighboring seller MGs.
- *Protection of seller interests :* In a seller level game, seller MGs are allowed to decide their strategy regarding the amount of energy they want to trade out of total surplus after adjusting their own energy consumptions. This in turn depends on the bid placed by BAA and the preference parameter of each seller MG.
- *Simple pricing mechanism :* Unlike the complex bidding algorithms used in literature [6] [7], we have used a simple pricing mechanism which makes overall system operation simple and reduces communication overhead to great extent. This also results into improved utility of both seller and buyer MGs.
- *Numerical analysis and discussion:* The extensive numerical analysis highlights the practical applicability and advantages of the proposed method.

The rest of the paper is organized as follows. The details related to the multi-microgrid cluster model are presented in section II. Various strategies for energy trading for both seller, as well as buyer MGs along with roles played by BAA and EMO, are summarized in section III. Numerical results and discussion are given in section IV. Finally, we conclude this paper in section V.

II. Multi-Microgrid Cluster Model

Consider a smart distributed network of multiple microgrids with various intelligent agents as shown in Fig. 1. All the MGs are interconnected and can exchange energy among themselves and with the main grid through dedicated power exchange lines. The necessary communication infrastructure is assumed to be present as given in [25], [26]. Let us assume that there are N MGs in a distributed network and they belong to the set $\mathcal{N}$. Each $n \in \mathcal{N}$ is equipped with DERs such as wind, solar PV etc. Each MG $i \in \mathcal{N}$ can generate energy G_i during certain fixed time interval of the day. Each MG is required to fulfill essential load demand of its consumers L_i^{min}. If $G_i > L_i^{min}$ for some MG $i \in \mathcal{N}$, this ith MG is considered as seller and P is set of all such seller MGs i.e. $P = \{i \in \mathcal{N} \mid G_i > L_i^{min}\}$. If $G_i < L_i^{min}$, this ith microgrid needs to buy extra energy either from seller microgrids or the

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main grid. This microgrid is termed as a buyer. Let Q be the index set of all such buyer MGs i.e., $Q = \{i \in \mathcal{N} \mid G_i < L_i^{min}\}$. The energy requirement of ith buyer MG is given as

$$E_{req,i} = \left|\left(G_i - L_i^{min}\right)\right| \qquad \forall i \in Q \tag{1}$$

and the total energy requirement of all buyer MGs is

$$E_{req} = \sum_{i \in Q} E_{req,i} \tag{2}$$

After serving its own essential loads, seller microgrid i will have excess energy for sell given as

$$E_{ex,i} = \left(G_i - L_i^{min}\right) \qquad \forall i \in P \tag{3}$$

and the total excess energy available from all seller MGs before adjusting their load consumption is

$$E_{extra} = \sum_{i \in P} E_{ex,i} \tag{4}$$

We assume that each seller microgrid $i \in P$ wants to manage its energy consumption L_i s.t. $L_i \geq L_i^{min}$ so that it can sell remainder of its generated energy $(G_i - L_i)$ to the buyer MGs or to the main grid using proposed energy trading mechanism.

The excess energy available from ith seller MG after adjusting its load consumption is given as

$$E_{ex,i}^{*} = (G_i - L_i) \qquad \forall i \in P \tag{5}$$

and the total excess energy available from all seller MGs after upgrading their individual load demand to L_i is

$$E_{extra}^{*} = \sum_{i \in P} E_{ex,i}^{*} \tag{6}$$

Here, we have considered G_{bp} and G_{sp} as grid buying and grid selling prices respectively. We assume that the unit cost of energy that BAA pays to each seller MG is set between G_{bp} and G_{sp}. Thus, it is clear that each seller MG is more interested in selling excess energy $E_{ex,i}^{*} \forall i \in P$ to neighboring buyer MGs rather than trading with the main grid. For each buyer MG, we will calculate its priority factor based on its historical contribution as well as local load demand. γ_i denotes priority factor of ith buyer MG. In order to highlight the importance of the priority factor, a weight factor μ is used.

A typical energy trading scenario, in which a set Q of buyer MGs requests energy from the set P of neighboring seller MGs via BAA is shown in Fig.1. The BAA gathers the total energy demand from all the buyer MGs i.e. E_{req} . The BAA then decides the per unit cost of energy ρ in order to buy required energy from seller MGs s.t. $G_{bp} \leq \rho \leq G_{sp}$. Looking at the price placed by BAA, each seller MG then adjusts its optimal energy consumption L_i, and makes remaining energy $E_{ex,i}^{*}$ $\forall i \in P$ available for sell and informs the EMO and BAA via SAA. The BAA then passes this information to all buyer MGs. Depending on the total excess energy available for sell E_{extra}^{*} and individual priority factor,

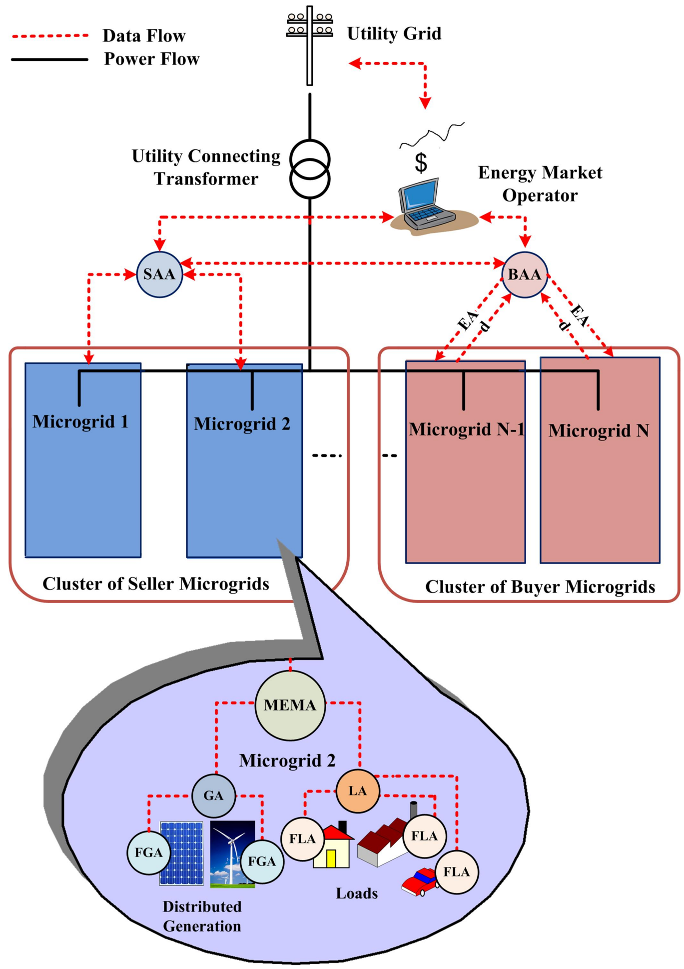

Fig.1. Proposed system architecture of a distribution network with multiple intelligent microgrids.

each buyer MG then decides its strategy d_i to request certain fraction of excess energy from EMO using algorithm 1 which uses non-cooperative game among buyer MGs. BAA then conveys this information to the EMO. After receiving strategies from all buyer MGs regarding energy demand, EMO uses algorithm 2 to allocate an appropriate amount of energy EA_i to individual buyer MGs based on the excess energy, demand and priority factor of buyer MGs. Therefore, the energy trading mechanism depicted in Fig.1 ensures simple, fair and stable energy trading among MG clusters. Since, demand for energy is the strategy of the buyer MG, d_i is not always equal to the actual energy need of the buyer MG i i.e. $E_{req,i}$. Each buyer MG decides its strategy d_i on [0, $E_{i,req}$] in order to maximize its energy allocated EA_i.

A. Utility of Seller MGs

The total utility achieved by each seller MG $i \in P$ from its own energy consumption L_i and from selling excess energy $E_{ex,i}^{*}$ to neighboring buyer MGs is given by,

$$U_{i \in P} = z_i \ln(1 + L_i) + \rho\,(G_i - L_i), \quad z_i > 0 \tag{7}$$

In literature the natural logarithm has been used extensively to measure user's satisfaction with decreasing returns [15],

[18]. In (7), first part represents the utility that each seller MG achieves from its own energy consumption L_i, where z_i is a preference parameter [15]. The seller MGs with higher value of z_i are more interested in consuming energy to serve L_i as compared to the seller MGs with lower value of z_i. The second part of (7) gives the revenue that seller MGs can earn by trading excess energy with neighboring buyer MGs.

Since BAA has no generation capacity; it needs to buy the entire energy demand of all buyer MGs either from the seller MGs or the main grid. In most of the cases, the main grid sells energy at higher rate compared to that from the MGs equipped with DERs such as feed – in tariff schemes [15]. Thus, BAA is more interested in buying energy on behalf of the entire buyer MGs from neighboring cluster of seller MGs at rate ρ and remaining, if any from the main grid. The careful selection of ρ is important. The too small value of ρ i.e. $\rho \leq G_{bp}$ will encourage seller MGs to utilize excess energy for its own use rather than trading with the neighbors. At the same time too high value of ρ i.e. $\rho \geq G_{sp}$ will cost buyers significantly. In case, if the energy from the seller MGs is not sufficient to fulfill energy demand of buyer MGs, BAA will buy the remaining energy from the main grid at G_{sp}.

The total cost incurred to the BAA for buying energy on behalf of all buyer MGs is given as

$$C_{BAA} = \left(\sum_{i\in P} E^*_{ex,i} * \rho\right) + \left(E_{req} - \sum_{i\in P} E^*_{ex,i}\right) * G_{sp} \qquad (8)$$

In (8), the first part shows the total cost while buying energy from neighboring seller MGs and the second part indicates the cost incurred while buying remaining energy from the main grid. The second part also shows that the BAA does not buy more than required energy and energy balance holds good at all time.

B. Utility of Buyer MGs

While deciding utility of buyer MG $U_{i\in Q}$, we assume that $U_{i\in Q}$ is always a non-negative real valued function. The energy requirement of each buyer MG is different; however each buyer wants to receive as much energy as possible from EMO, limited to the required energy of buyer MG. Thus, utility of buyer MG i is defined in terms of the energy allocated (EA_i) by EMO. The utility of buyer MGs must be a strictly increasing function of $\frac{EA_i}{d_i}$ i.e. satisfaction increases by the ratio between energy allocated and energy demand [18]. Also $U_{i\in Q}$ must be a concave function of EA_i because increasing rate of satisfaction decreases as the energy allocated increases. Finally, the energy allocation should also directly proportional to the priority factor and depends on the weight factor of the priority. Thus, the utility function of buyer MG is defined as,

$$U_{i\in Q} = \gamma_i^{\mu} \log\left(1 + \frac{EA_i}{d_i}\right) \quad , s.t. \, 0 \leq EA_i \leq d_i \qquad (9)$$

where, d_i is the strategy of the ith buyer MG.

III. Strategies For Energy Trading

In this section we will discuss the strategies adopted by BAA, EMO, seller and buyer MGs in order to maximize their utilities. The aim of each seller MG is to adjust its own energy consumption to maximize its utility in (7) by looking at the price placed by the BAA. The goal of the BAA is to minimize per unit cost of energy while purchasing energy from seller MGs. At the same time, each buyer MG wants to acquire as much energy as possible to fulfill its local load demand. The roles played by BAA and EMO are also discussed in detail.

A. Buyer Strategies

In order to sustain energy trading among neighborhood MGs, there must exist some incentive mechanism for the participating MGs which will encourage local energy trading. Thus, we have used the priority factor [19] to prioritize buyer MGs while distributing excess energy.

- *Calculation of Priority Factor*

For each buyer MG, we will calculate its priority factor $\gamma_i \ \forall i \in Q$ using (10).

$$\gamma_i = \frac{C_i}{C_{Total}} + \frac{D_i}{D_{Total}} \qquad (10)$$

In (10), C_i represents the number of contributions recorded by a buyer MG till present interval, C_{Total} is the total number of contributions recorded by EMO till current interval, D_i gives the load demand from buyer MG i and D_{Total} represents load demand of all buyer MGs in the current interval. The first part in (10) measures the contributions made by MG in past by selling its excess energy to neighboring MGs and second part quantifies the load demand in each buyer MG. Since equal importance is given to both past contributions made as well as local load demand, MGs gets encouraged to trade energy among themselves rather than trading with the main grid. We have also used a weight factor μ ($\mu > 0$) which indicates importance of priority factor during energy trading. It is dynamic in nature and set by EMO. However, in this study, we set value of μ as 1.5 for all buyer MGs.

- Non-cooperative Game among Buyer MGs

Each buyer MG is a rational player and having different energy demands. Also, each one is trying to acquire as much energy as possible from the local energy market via EMO. Thus, the utility functions of all buyer MGs is given as,

$$u(d) = \underset{EA}{argmax} \left[\sum_{i\in Q} \gamma_i^{\mu} \log(1 + \frac{EA_i}{d_i})\right] \qquad (11)$$

$$\text{s. t.} \qquad 0 \leq EA_i \leq d_i, \ \forall i \in Q$$

$$\sum_{i\in Q} EA_i \leq E^*_{extra}$$

where d_i is the demand strategy of ith buyer MG. The competition among buyer MGs is formulated as a non-cooperative continuous strategic form of game $G = (d_i, u_i)_{i=1}^{Q}$. Here |Q| is the total number of buyer MGs and u_i

is a payoff function and $d_i = [0, E_{i,req}]$ is the strategy for each buyer MG $i \in Q$.

In order to show the existence of the NE in buyer level game, we need to show the continuity and quasi- concavity of the utility function [30]. As the objective function is continuous and the strategic domain is convex, it is clear that the utility function $u_i(d_1, d_2 \dots, d_Q)$ is continuous in $(d_1, d_2 \dots, d_Q)$.

Now to prove quasi-concavity, for a buyer MG i, fix the other buyer MGs strategies $d_{-i} = \bar{d}_{-i}$. Let us consider three arbitrary strategies d_i'', $\bar{d}_i$, and d_i' such that $d_i'' < \bar{d}_i < d_i'$. To prove quasi-concavity of the utility function in d_i, it is enough to show [18]

$$\min\{u_i(d_i'', \bar{d}_{-i}), u_i(d_i', \bar{d}_{-i})\} \leq u_i(\bar{d}_i, \bar{d}_{-i}).$$

If any one of the utilities $u_i(d_i'', \bar{d}_{-i})$, and $u_i(d_i', \bar{d}_{-i})$ is zero, then the proof is done. Therefore, now we will consider a nontrivial case when both of them are nonzero.

Case A: $u_i(\bar{d}_i, \bar{d}_{-i}) = 0$

In this case $u_i(d_i', \bar{d}_{-i}) = 0$ and therefore the inequality holds.

Case B: $u_i(\bar{d}_i, \bar{d}_{-i}) = \bar{d}_i$

In this case, it can be proved that $u_i(d_i'', \bar{d}_{-i}) = d_i''$ by the similar way in Lemma 1 [18], therefore

$\min\{u_i(d_i'', \bar{d}_{-i}), u_i(d_i', \bar{d}_{-i})\} \leq d_i'' < u_i(\bar{d}_i, \bar{d}_{-i})$.

Case C: $0 < u_i(\bar{d}_i, \bar{d}_{-i}) < \bar{d}_i$.

By Lemma 1 [18], $u_i(\bar{d}_i, \bar{d}_{-i}) \geq u_i(d_i', \bar{d}_{-i})$ which completes the proof for the quasi-concavity of the utility function in d_i. By using Lemma 2 [18] and Theorem 2.2 in [30], the existence of NE can be directly shown as below.

Let us consider $d^* = \{d_1^*, \dots, d_N^*\}$ is a NE of the proposed non-cooperative Game among Buyer MGs, which is given by

$$d_i^* = \min\{\psi^* \gamma_i^{\mu}, E_{req,i}\}$$

Where ψ^* is a number satisfying $\sum_{i\in Q} d_i^* = E_{extra}^*$.

Proof: for $i \in Q$, we need to show

$$u_i(d_i^*, d_{-i}^*) \geq u_i(d_i, d_{-i}^*) \qquad \forall d_i \in [0, E_{req,i}].$$

As $\sum_{i\in Q} d_i^* = E_{extra}^*$ gives $u_j(d^*) = d_j^* \ \ \forall j \in Q$.

If $d_i \leq d_i^*$, it can be observed that

$$u_i(d_i, d_{-i}^*) \leq d_i \leq d_i^* = u_i(d_i^*, d_{-i}^*).$$

The case remain to prove is that when $d_i > d_i^*$. If $d_i^* = E_{req,i}$, then there is no strategy larger than d_i^*, then it remains the case $d_i^* = \psi^* \gamma_i^{\mu}$.

Suppose there are at least two buyer MGs of which utility is less than the amount of their own strategy; i.e.,

$$\exists i, j \in Q \ s.t. \ u_i(d^*) < d_i^* \text{ and } u_j(d^*) < d_j^*.$$

Then d^* is a unique NE solution in the proposed buyer MG level game [18].

Proof: Let us suppose there exists another NE, say $d' = \{d_1', \dots, d_N'\}$. If there is $x \in Q$ such that $u_x(d') < d_x^*$, then by using proposition 2 [18], it is not a NE as $u_x(d_x^*, d_{-i}') = d_x^*$. If there is $x \in Q$ such that $u_x(d') > d_x^*$, then there has to exists $y \in Q$ such that $u_y(d') < d_y^*$ because $u_n(d^*) = d_n^*$ for all $n \in Q$ and $\sum_{n\in Q} d_n^* = E_{extra}^*$; is not a NE either. Therefore it is concluded $u_x(d') = d_x^*$ for all $\in Q$.

Also, if $\sum_{j\in Q} d_x' < \sum_{j\in Q} d_x^*$, then $\sum_{x\in Q} d_x' < E_{extra}^*$ which is a contradiction. Therefore, it remains the case when $\sum_{j\in Q} d_j' \geq \sum_{j\in Q} d_j^*$. Since $d' \neq d^*$, there is $i \in Q$ such that $d_i^* < d_i'$. Let $\bar{d}_i$ be a strategy between them, i.e., $d_i^* < \bar{d}_i < d_i'$. Since $u_i(d_i^*, d_{-i}') = u_i(d_i', d_{-i}') = d_j^*$, it can be observed from the quasi–concavity of the utility function that $u_i(\bar{d}_i, d_{-i}') = d_j^*$. Also, $0 < u_i(\bar{d}_i, d_{-i}') < \bar{d}_i$. Now, by using Lemma 1[18], we can show that $u_i(\bar{d}_i, \bar{d}_{-i}) > u_i(d_i', \bar{d}_{-i})$, which also contradicts with the assumption made i.e. d' is an NE.

Thus, there exists only a unique NE in the proposed non-cooperative game among buyer MGs. The algorithm 1 gives the NE solution i.e. the optimal strategy for each buyer MG.

Algorithm 1 : Optimal Strategy for Buyer MG

Initialization:

- Collect energy requirements from all buyer MGs along with their priority factors i.e. γ.
- Arrange all buyer MGs and their γ vector by the value of $\frac{E_{req,i}}{\gamma_i^{\mu}}$ in ascending order.
- Initialize filling index j = 1; N= |Q| ;

Filling width $w = \sum_{i\in Q} \gamma_i^{\mu}$;

Energy remaining $E_{rm} = E_{extra}^*$;

Energy height η = 0;

$E_{req,N+1} = \infty$ and $\gamma_{N+1} = 1$ for handling exceptional case

While $\{E_{rm} > 0\}$

- **if** $\left\{w\left(\frac{E_{req,j}}{\gamma_j^{\mu}} - \eta\right) < E_{rm}\right\}$

$E_{rm} = E_{rm} - w\left(\frac{E_{req,j}}{\gamma_j^{\mu}} - \eta\right)$;

$\eta = \frac{E_{req,j}}{\gamma_j^{\mu}}$; $w = w - \gamma_j^{\mu}$; $d_j = E_{req,j}$;

j = j + 1 ;

- **else**

$\eta = \eta + \frac{E_{rm}}{w}$; $E_{rm} = 0$;

for k = j: N

$d_k = \eta\, \gamma_k^{\mu}$;

End

Rearrange the optimal strategy of each buyer microgrid in original order.

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- Role of BAA

The BAA is acting as the representative of all buyer MGs. The main function of BAA is to decide per unit cost of energy, ρ in order to buy required energy $E_{req} = \sum_{i\in Q} E_{req,i}$ from seller MGs s.t. $G_{bp} \leq \rho \leq G_{sp}$. The BAA has no control over G_{bp} and G_{sp}, thus it has to adjust its own buying price ρ to minimize (8). The objective of the BAA is given as,

$$\min_{\rho} C_{BAA} \tag{12}$$

Now, using the first order optimality condition of BAA's objective function in (8), we have

$$\frac{\delta C_{BAA}}{\delta \rho} = 0 \tag{13}$$

Solving (13), we get

$$\rho = \begin{cases} \sqrt{\frac{G_{sp}\sum_{i\in P} z_i}{P+\sum_{i\in P} G_i}} & if\ \rho > G_{bp} \\ G_{bp} + \vartheta & otherwise \end{cases} \tag{14}$$

where $\vartheta > 0$ is a small value to keep ρ more than G_{bp}.

B. Seller Strategies

We have assumed that seller MGs do not have any storage capacity therefore each seller MG is interested in selling its excess energy $E^*_{ex,i} = (G_i - L_i)\ \ \forall i \in P$ at suitable price ρ to the BAA after adjusting its own energy consumption L_i. Thus, the objective of each seller MG is

$$\max_{L_i} U_{i\in P} \quad ,$$

$$\text{s.t. } L_i \geq L_i^{min} . \tag{15}$$

from (7) and (15), the first order differential condition for maximum utility can be derived as

$$\frac{z_i}{1+L_i} - \rho = 0 \tag{16}$$

Solving (16) further gives

$$L_i = \frac{z_i}{\rho} - 1 \quad . \tag{17}$$

From (17), we can observe the decision making process of each seller MG is influenced by the price set by BAA. Care should be taken such that z_i is sufficiently large so that (17) always possesses a positive value for all resulting values of L_i. Also, L_i should be at least as large as its minimum essential load. From (17) it is also clear that the energy consumption L_i of each seller MG is inversely proportional to the price per unit of energy set by BAA. Hence, higher value of ρ, encourages seller MGs to sell more energy by reducing its own energy consumption and *vice-versa*.

Algorithm 2 : EMO Energy Allocation Algorithm

Initialization:

- Collect data of all buyer MGs along with their strategy vector d and γ. N = |Q|
- Arrange the buyer MGs and their corresponding strategy vector d and γ by the value of $\frac{d_i}{\gamma_i^\mu}$ in ascending order.
- Initialize the filling indexes j = 1 and k = 2, filling width w = γ_1^μ, energy remaining $E_{rm} = E^*_{extra}$, energy height h = $\frac{d_1}{\gamma_1^\mu}$, energy allocated vector of all buyers EA = 0, $d_{N=1} = \infty$ and $\gamma_{N+1} = \infty$ for handling exception case

While {E_{rm}**> 0** }

- **if** $\{\frac{2d_j}{\gamma_j^\mu} > \frac{d_k}{\gamma_k^\mu}\}$ & $\{w\left(\frac{d_k}{\gamma_k^\mu} - h\right) < E_{rm}\}$,

$E_{rm} = E_{rm} - w\left(\frac{d_k}{\gamma_k^\mu} - h\right)$;

$w = w + \gamma_k^\mu$; $h = \frac{d_k}{\gamma_k^\mu}$; k = k + 1;

- **else if** $\{\frac{2d_j}{\gamma_j^\mu} \leq \frac{d_k}{\gamma_k^\mu}\}$ & $\{w\left(\frac{2d_j}{\gamma_j^\mu} - h\right) < E_{rm}\}$,

$E_{rm} = E_{rm} - w\left(\frac{2d_j}{\gamma_j^\mu} - h\right)$;

$EA_j = d_j$; w = $w - \gamma_j^\mu$; $h = \frac{2d_j}{\gamma_j^\mu}$;

j = j + 1;

- **else ,**

$$h = h + \frac{E_{rm}}{w} ;\ E_{rm} = 0;$$

for i = $j : k$

$EA_i = \gamma_i^\mu \left(h - \frac{d_i}{\gamma_i^\mu}\right)$;

End

Rearrange the allocated energy EA in original order and distribute among buyer microgrids.

C. Role of EMO

The main function of EMO is to distribute excess energy available from seller MGs among buyer MGs. The EMO wants to maximize the social welfare (SW) i.e. the sum of the satisfaction of all buyer MGs. Let $U_i(EA_i)$ is the satisfaction of buyer i from EMO's view. $\sum_{i\in Q} U_i(EA_i)$ is the SW of the system. Now the optimization problem to allocate energy to the buyer MGs is given as

$$\max_{EA} \sum_{i\in Q} \gamma_i^\mu \log 1 + \frac{EA_i}{d_i} \tag{18}$$

$$\text{s.t.} \quad 0 \leq EA_i \leq d_i \qquad \forall i \in Q$$

$$\sum_{i\in Q} EA_i \leq E^*_{extra}$$

By using Theorem (1) in [18], the optimal energy allocation $EA^* = \{EA_i^* \mid i \in Q\}$ is given as

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TABLE II
SYSTEM DATA AND STRATEGIES ADAPTED BY SELLER MGS AND BAA ($G_{sp} = 2.4\, cents/kWh$, $G_{bp} = 0.8\, cents/kWh$)

BLK	MG	LOAD (L^{min}) (kW)	Gen. (G) (kW)	(G- L^{min}) (kW)	Role	Preference parameter of seller MG (z_i)	ρ (cents/kWh) Set by BAA	Actual Energy Consumption of Seller MGs (L) (kW)	E_{ex}^* (kW)
1	1	70	90	+20	Seller	140	1.90	72.74	+17.26
	2	50	80	+30	Seller	125		64.79	+15.21
	3	100	70	-30	Buyer	-		-	-
	4	80	30	-50	Buyer	-		-	-
	5	90	70	-20	Buyer	-		-	-
	6	70	100	+30	Seller	145		75.32	+24.68
2	1	90	50	-40	Buyer	-	1.59	-	-
	2	80	140	+60	Seller	135		83.90	+56.10
	3	90	130	+40	Seller	150		93.33	+36.67
	4	110	50	-60	Buyer	-		-	-
	5	120	90	-30	Buyer	-		-	-
	6	100	70	-30	Buyer	-		-	-
3	1	70	110	+40	Seller	130	1.70	75.51	+34.49
	2	60	100	+40	Seller	125		72.53	+27.47
	3	110	50	-60	Buyer	-		-	-
	4	100	80	-20	Buyer	-		-	-
	5	140	140	0	-	-		-	-
	6	90	40	-50	Buyer	-		-	-
4	1	80	100	+20	Seller	145	1.73	82.82	+17.18
	2	100	70	-30	Buyer	-		-	-
	3	70	120	+50	Seller	130		74.14	+45.86
	4	70	100	+30	Seller	140		79.92	+20.08
	5	70	110	+40	Seller	125		71.25	+38.75
	6	120	70	-50	Buyer	-		-	-

$$EA_i^* = \begin{cases} h\gamma_i^{\mu} - d_i & if\ this\ is\ > 0\ and\ < d_i \\ d_i & if\ the\ above\ value\ is\ \geq\ d_i \\ 0 & otherwise \end{cases} \tag{19}$$

Here h is the real number such that $\sum_Q EA_i^* = E_{extra}^*$

The above problem is the different version of water filling problem in [29]. The algorithm 2 gives the optimal solution of the above problem using modified water filling algorithm given in [18].

IV. NUMERICAL RESULTS

For numerical case study purpose, we have considered a distributed network of six interconnected MGs. The 24 hours of a day are divided into 96 blocks of 15 min each. However, EMO is supposed to decide this time interval depending on the operating circumstances. The selection of short duration is normally preferred as the amount of energy available for sell is directly proportional to the trading interval. During this fixed time interval, we assume that demand and supply are constant. The first 5 minutes are designated as discussion period for inter-agent communications for negotiating energy trading for next interval. The result of these negotiations is a set of mutual contracts which will be implemented in the next trading interval. The system data used for first 4 time blocks are given in Table II. The values of G_{bp} and G_{sp} are set as 0.8 USA cents/kWh and 2.4 USA cents/kWh respectively [17]. The value of μ is fixed at 1.5. For this study, preference parameter z_i is selected as a random variable from the range [120, 150].

In block 1, MGs 1, 2 and 6 have generated energy more than their minimum loads requirements whereas, MGs 3, 4 and 5 have generated energy less than their minimum load. Therefore, MGs 3, 4 and 5 register themselves as buyers at BAA and forms a cluster of buyer MGs whereas MGs 1, 2 and 6 register themselves as sellers at SAA and forms a cluster of seller MGs. The BAA has the information regarding buyer energy requirements, seller generations, and their preference parameters. Based on this information, BAA calculates bid value on behalf of all the buyers using (14) which is 1.90 cents/kWh during the first interval. By looking at the price set by BAA, seller MGs adjusts their energy consumption and puts remaining energy for sell. During first interval MGs 1, 2 and 6 have updated their energy consumption to 72.74 kW, 64.79 kW and 75.32 kW respectively and hence total excess energy available for trade is 57.15 kW.

In order to sustain energy trading, EMO calculates priority factor for each buyer MG. Based on priority factor, each buyer decides its optimal strategy to buy energy from the surplus. During the first interval no past contributions are recorded, hence the second part of (10) only dominates. During this interval, MG with more load demand will get more priority. It can be observed that MG 4 having highest load demand of 50 kW gets higher priority, i.e. 0.5 and MG 5 is having lowest load demand gets lower priority of 0.2. Based on total energy remaining for sell and priority factor, each buyer calculates its optimal strategy for buying energy from the surplus. In block 1, MGs 3, 4 and 5 calculates their optimal strategies as 15.46 kW, 33.27 kW and 8.42 kW respectively using algorithm 1. Once the strategies are calculated by individual buyer MG, it will be forwarded to the EMO via BAA. After receiving the optimal strategies from individual buyer MG, EMO uses algorithm 2 to allocate energy to the buyer MGs proportional to their priority factor. Since MG 4 is having highest priority during first interval, it gets highest allocation of energy from the EMO as 33.27 kW. MG 5 is assigned with lower priority factor gets lowest energy share of 8.42 kW.

In block 1, seller MG 6 is having highest preference parameter as 145 which in turn indicate its inclination towards more self-energy consumption rather than trading with the neighboring MGs. MG 6 is having a minimum load of 70 kW which it adjusts to 75.32 kW after receiving a bid value of 1.90 cents/ kWh from the BAA. Similarly, MG 1 and MG 2 are having preference parameters140 and 125 which in turn adjust their energy consumptions to 72.74 kW and 64.79 kW from earlier 70 kW and 50 kW respectively. In block 1, total energy demand is 100 kW. However, total available excess energy from neighboring seller MGs is only 57.15 kW. Thus, BAA requests EMO to buy remaining 42.85 kW of energy from the Main grid at G_{sp} rate.

The overall energy trading scenario during first four blocks of the time interval is depicted in table III. In block 2, MG 2 and 3 are acting as sellers whereas MG 1, 4, 5 and 6 are acting as buyers. Since MG 1 has acted as seller and contributed its excess energy in past interval i.e. in block 1, this MG will receive more importance in the second interval in terms of priority during energy allocation. It is clear that MG 1 receives 32.47 kW of energy which is higher than rest of the buyer MGs. Thus, the proposed mechanism encourages the MGs to share excess energy among themselves rather than trading with the main grid.

In block 3, we have two seller MGs and three buyer MGs. Since generation and load are equal in MG 5, this MG remains energy neutral. In block 4, there are four seller MGs whereas buyers are only two. Also, excess energy for sell is around 121.87 kW which is far more than the buyer's demand of 80 kW. Thus, after fulfilling local MGs demand, excess energy of 41.87 kW will be sold to the main gird at rate G_{bp}. As the trading goes on, EMO continues to record the contributions made by individual MG which helps it in calculating their priority factors in future.

The number of microgrids versus average convergence time for algorithm 1 and algorithm 2 is depicted in figures 2 and 3 respectively as a number of participating MGs varies from 4 to 100. However, in most of the practical cases, the number of MGs participating in energy trading will be well below 50. All simulations are performed on 2.53 GHz Intel core i3 processor. The average convergence time is a linearly increasing function of number of participating MGs. In a case of minimum four participating MGs, the average convergence time for Algorithm 1 and Algorithm 2 is 2.1 ms and 2.4 ms respectively. Also, in extreme case of 100 participating MGs, the average convergence time turns out to be only 0.2 and 0.65 seconds, respectively. This justifies the selection of 5 minutes as discussion period at the beginning of the trading.

The Fig. 4 illustrates the effect of the variation of the weight factor μ on the energy allocated to the buyer MGs in interval 2. When the weight factor is zero, the equal amount of energy is allocated to each buyer MG, in this case, 23.19 kW. This is because when $\mu = 0$, EMO does not consider the importance of the priority. As we go on increasing the value μ, the

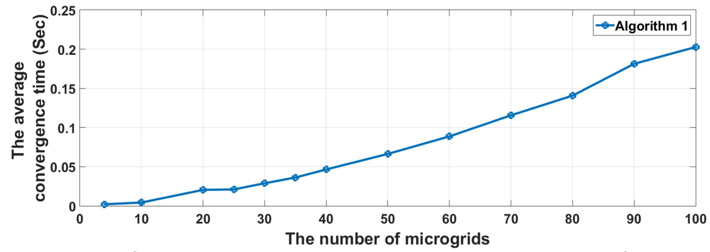

Fig.2. Number of microgrids versus the average convergence time for Algorithm 1

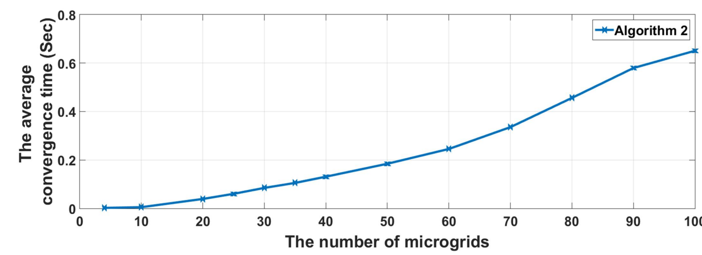

Fig.3. Number of microgrids versus the average convergence time for Algorithm 2

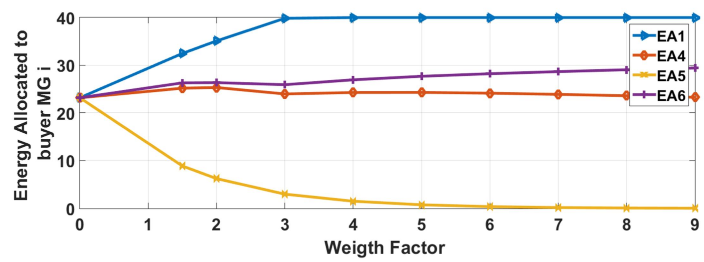

Fig.4. Effect of variation in the weight factor μ on energy allocated to buyer MG's

energy allocation gap also goes on increasing until the buyer with the higher priority gets saturated to its maximum.

In order to highlight the benefits of the proposed mechanism, the results are also compared with the Multi-leader Multi-follower (MLMF) based distributed mechanism suggested in [17] as simulation setup is close to the proposed method. The optimal bid placed by BAA during various trading intervals is shown in Fig. 5. It is interesting to note that in both methods, optimal bids are within the limits i.e. $G_{bp} \leq \rho \leq G_{sp}$. In MLMF method [17] optimal bid monotonically increases with the number of buyer MGs. In worst case of two buyer MGs i.e. in block 4, the optimal bid for [17] turns out to be only 0.8/kWh which is equal to the grid buying price. In almost all blocks, the bid placed by BAA using proposed method is higher than the MLMF method. This in turn encourages seller MGs to share more portion of their excess energy with the buyers and also increases utility of seller MGs.

Figures 6 to 9, shows the energy allocation to the buyer MGs during various trading intervals. In MLMF [17] method, each buyer receives the equal share of the excess energy. Thus, there is no distinction among the buyer MGs. Also, irrespective of the load demand, each buyer MG receives the equal share of the excess energy. Contrast to this, in the proposed mechanism, the energy is allocated to individual buyer MG proportional to its priority factor which in turn depends on its local load demand and past contributions

TABLE III
OVERALL ENERGY TRADING SCENARIO IN A DISTRIBUTED NETWORK OF SIX MICROGRIDS

BLK	E^{*}_{ex} (Total Excess Energy for sell in kW)	E_{req} (Energy Required in kW)	γ (Priority Factor)	Optimal strategy of Buyer MGs (Energy Requested in kW)	EMO Decision (Energy Allocated in kW)	Energy exchanged with main grid E_{xm} (kW)
1	57.15	[0 0 30 50 20 0]	[0 0 0.3 0.5 0.2 0]	[0 0 15.46 33.27 8.42 0]	[0 0 15.46 33.27 8.42 0]	-42.85
2	92.77	[40 0 0 60 30 30]	[0.45 0 0 0.38 0.19 0.39]	[32.47 0 0 25.20 8.90 26.20]	[32.47 0 0 25.20 8.90 26.20]	- 67.23
3	61.96	[0 0 60 20 0 50]	[0 0 0.60 0.15 0 0.53]	[0 0 31.69 3.96 0 26.31]	[0 0 31.69 3.96 0 26.31]	- 68.04
4	121.87	[0 30 0 0 0 50]	[0 0.65 0 0 0 0.72]	[0 30 0 0 0 50]	[0 30 0 0 0 50]	+41.87

(-) indicates energy imported from the main grid and (+) indicates energy exported to the main grid

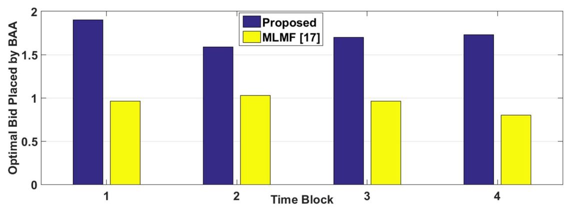

Fig.5. Optimal bid placed by BAA during various trading intervals

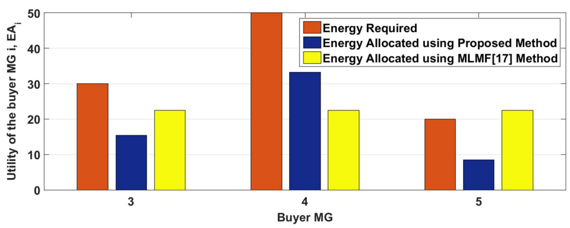

Fig.6 Energy requirement and energy allocated to various buyer MGs in block interval 1

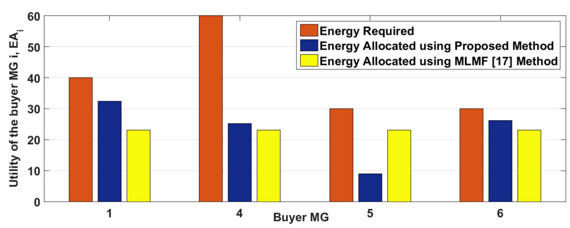

Fig.7 Energy requirement and energy allocated to various buyer MGs in block interval 2

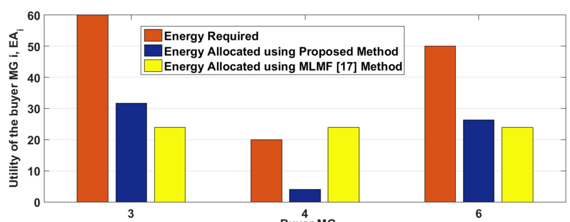

Fig.8 Energy requirement and energy allocated to various buyer MGs in block interval 3

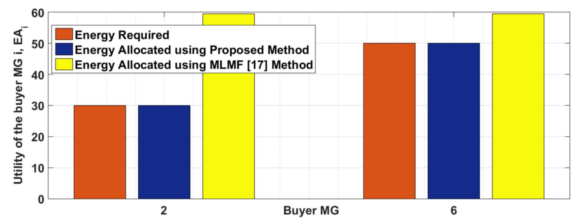

Fig.9 Energy requirement and energy allocated to various buyer MGs in block interval 4

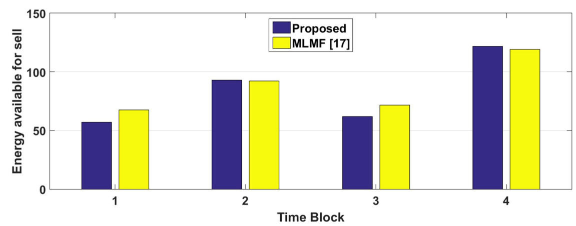

Fig.10 Excess energy available with seller MGs at various trading intervals

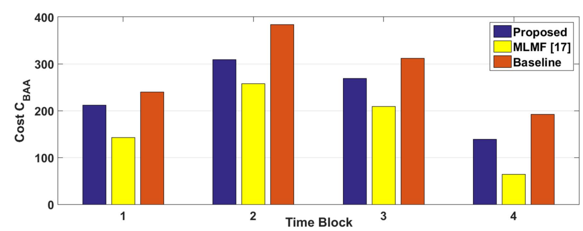

Fig.11 Total cost incurred to BAA while fulfilling buyers demand during various trading intervals

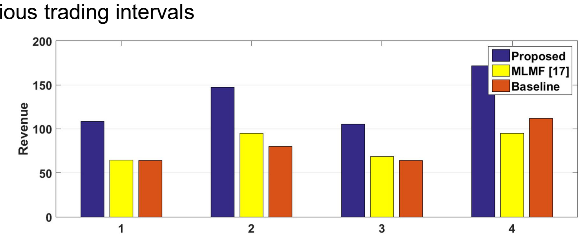

Fig.12 Total revenue earned by seller MGs during various trading intervals

recorded and limited to its maximum demand. Thus, unlike the method in [17], the proposed method ensures proactive energy sharing among local MGs clusters.

The excess energy available for trade during various trading intervals is shown Fig. 10. Unlike the reported work [17]-[19], we have paid attention to the seller strategies as well. As a result, sellers are allowed to use some portion of the excess energy for running their own elastic loads. Therefore, even after using some portion of excess energy for running elastic load, the remaining energy available for trade is close to the results obtained using MLMF method [17]. The total cost incurred to BAA i.e C_{BAA} while fulfilling buyers demand during various trading intervals is depicted in Fig. 11. As the bid placed by BAA using [17] is less than the proposed method, the C_{BAA} is more for the proposed method. However, it is less than the baseline approach. Higher value of C_{BAA} encourages seller MGs to trade larger portion of their excess energy in local market. The total revenue earned by seller MGs during various trading intervals is shown in Fig. 12. As the bid place by BAA using proposed method is higher than the MLMF [17] and grid buying price, a substantial improvement in the revenue earned by seller MG is observed. Thus, proposed method protects the interests of seller MGs as well. Also, seller MGs are allowed to run their own elastic loads.

It is interesting to note that in table III, each buyer MG follows the Nash equilibrium (NE) strategy. Hence, the strategy submitted by each buyer MG and energy allocated by EMO are always equal as shown in Table III. However, if there exist any selfish player who submits other than Nash equilibrium solution as strategy, EMO ensures fair energy allocation to each buyer MG who follows NE solution based on its priority factor. Thus, selfish behavior of any buyer MG gets eliminated and the system remains stable. This ensures that interests of all buyer MGs also gets protected.

V. Conclusion and Future Work

In the proposed method interests of both the seller as well as the buyer microgrids are protected by allowing them to decide their own strategies to maximize their respective utilities. In order to promote local energy trading, incentives are given to the seller microgrids in terms of priority in future when they need energy from the local market. The seller microgrids are also allowed to decide the amount of energy they want to share out of their total surplus. The competition among buyer microgrids is formulated as a non-cooperative game. The existence and uniqueness of NE are also shown. Using proposed method, selfish behavior of any buyer microgrid gets eliminated. Introduction of simple pricing mechanism bypasses the use of complex bidding algorithms. The extensive numerical study quantifies the benefits of the proposed method as compared to the baseline and MLMF [17] method. Moreover, the distributed decision-making capability of an individual entity in the proposed framework has further reduced the communication overhead to a great extent.

The future work could focus on studying the effect of distributed storage and seasonal weather variation on the performance of the multi-microgrid distribution network managed using proposed mechanism.

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