# Multiagent-Based Energy Trading Platform for Energy Storage Systems in Distribution Systems With Interconnected Microgrids

H. S. V. S. Kumar Nunna, *Member, IEEE*, Anudeep Sesetti, Akshay Kumar Rathore, *Senior Member, IEEE*, and Suryanarayana Doolla, *Senior Member, IEEE*

***Abstract*—In this article, an agent-based transactive energy (TE) trading platform to integrate energy storage systems (ESSs) into the microgrids' energy management system is proposed. Using this platform, two different types of energy storage market models are proposed to promote local-level (within the microgrid) and communal- or global-level ESSs' participation in the intra- and intermicrogrid TE markets. Also, a reinforcement learning algorithm known as simulated-annealing-based $Q$-learning is used to develop bidding strategies for ESSs to participate in the TE markets. Besides energy trading, the proposed system also accounts for the losses caused by energy transactions between ESSs and microgrids using a complex current-tracing-based loss allocation method. The overall efficacy of the proposed energy market management system is demonstrated using a modified IEEE 123-bus distribution system with multiple microgrids and ESSs. Based on simulation results, it is observed that the proposed model can effectively reinforce the balance between the supply and the demand in the microgrids using the mix of local and global ESSs.**

***Index Terms*—Electricity markets, energy storage systems (ESSs), microgrids, multiagent systems, transactive energy (TE).**

## NOMENCLATURE

| | |
|---|---|
| CDA | Continuous double auction. |
| CESS | Centrally located energy storage systems. |
| DER | Distributed energy resource. |
| DESS | Distributed energy storage systems. |
| DG | Distributed generator. |
| DI | Demand interval. |
| DSO | Distribution system operator. |
| ESS | Energy storage system. |
| GACA | Global energy auction conducting agent. |
| GenA | Generator agent. |
| GSPA | Generalized second price auction. |
| JADE | Java agent DEvelopment. |
| LoadA | Load agent. |
| MACA | Microgrid energy auction conducting agent. |
| MSMA | Microgrid storage market agent. |
| PTDF | Power transfer distribution factor. |
| SAQL | Simulated-annealing-based $Q$-learning. |
| SMA | Storage market agent. |
| SOC | State of charge. |
| StrA | Storage agent. |
| TE | Transactive energy. |
| UA | Utility agent. |

Manuscript received May 7, 2019; revised August 13, 2019; accepted October 17, 2019. Date of publication March 9, 2020; date of current version April 24, 2020. Paper 2019-IACC-0553.R1, presented at the 2018 IEEE Industry Applications Annual Meeting, Portland, OR, USA, Sep. 23–27, and approved for publication in the IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS by the Industrial Automation and Control Committee of the IEEE Industry Applications Society. This work was supported by Nazarbayev University, Nur-Sultan, Kazakhstan, through Social Policy Grant. *(Corresponding author: Suryanarayana Doolla.)*

H. S. V. S. Kumar Nunna is with Nazarbayev University, Nur-Sultan 010000, Kazakhstan (e-mail: sivanand.nunna@nu.edu.kz).

Anudeep Sesetti is with Digital Business Unit, Enphase Energy, Bangalore 560017, India (e-mail: anudeep.sesetti@gmail.com).

Akshay Kumar Rathore is with the Department of Electrical and Computer Engineering, Concordia University, Montreal, QC H3G 1M8, Canada (e-mail: akshay.rathore@concordia.ca).

Suryanarayana Doolla is with the Department of Energy Science and Engineering, Indian Institute of Technology Bombay, Mumbai 400076, India (e-mail: suryad@iitb.ac.in).

Color versions of one or more of the figures in this article are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TIA.2020.2979782

## I. INTRODUCTION

MICROGRIDS with intermittent DGs and inelastic loads pose significant challenges to the microgrid operators in terms of real-time energy management. Imbalances arose can be handled by inclusion of appropriate-size ESSs or through enrollment of loads in demand response programs or a combination of both. The overall energy management can also be done by operating microgrids as a cluster or a virtual power plant [1], [2]. In the USA, demand response and ESSs can compete and participate in the wholesale electricity market along with the generators as per the orders (719 and 890) passed by the Federal Energy Regulatory Commission [3]. This paved a way in using ESSs to shape the load curves and to provide ancillary services more often. Large CESSs are, in general, used for ancillary service support in bulk transmission lines, whereas the small-scale DESSs are typically community level and used to control the overloading of distribution network elements, such as transformers and feeders [4]–[7].

ESSs coupled with renewable-energy-based distributed generation units help in increasing the potential of the renewable plant by their energy-buffering action [8]. ESSs can be installed at various locations, such as along the transmission network for ancillary power and VAR control, or at the distribution level for peak shaving and stress reduction on system assets and at the consumer level for trimming off the load fluctuations [9]. For example, Oh [10] proposed an optimal power flow approach to utilize ESSs in power transmission network applications with and without locational constraints. In this approach, the combined optimization of DGs and ESSs was not given enough focus, and the proposed methodology demands large computational time. A day-ahead scheduling framework for storage systems along with a detailed comparison of DESSs with CESSs' installations, including transmission constraints, was presented in [11]. The proposed model co-optimized the charging and discharging schedules of CESSs for maximizing the profit of the storage systems, and the approach was later extended to aggregated DESSs.

Recently, market-based control of renewable-energy-driven systems, such as microgrids, has a gained significant attention of both researchers and utility operators. Also, a notable number of attempts were reported in the literature on establishing on-site energy markets that dictate energy injections by DGs into the system [12]–[18]. Some of these attempts extended the concept to ESSs, such as the works presented in [13]–[16]. For example, the work presented in [13] introduces the concept of virtual storage management (modeling each ESSs as two independent substorages) to address energy imbalances caused by the intermittent nature of the renewable generation in the microgrid market environment. Morstyn *et al.* [15] present a novel market structure to integrate the demand flexibility of prosumers with ESSs and inelastic loads into the distribution-level TE management. In this article, the prosumer can be a residential consumer or a microgrid with elastic/inelastic energy resources. ESSs of the prosumers are modeled as flexible demand resources governed by their operating limits. The DSO purchases the demand flexibility of the prosumers on day-ahead basis and uses it in the overall management of the distribution system. Davison *et al.* [16] present a TE market model suitable for peer-to-peer energy transactions. In this model, each node in the system is modeled as a combination of generation, load, and energy storage and is delegated by an agent. ESSs connected to each node are used to manage the energy locally or to offer the energy service to neighboring nodes.

Although a significant number of market models for ESSs exist, an effective market mechanism that provides adequate motivation for private players to join the decentralized energy market as owners of DERs, such as ESSs, is still missing. Such mechanisms should visualize the storages as prosumers, i.e., energy sinks during excess power periods and sources during the power deficit periods irrespective of their location and adherence. Using this framework, ESSs located anywhere in the system can participate in the energy management of microgrids, if their participation is viable both technically and economically. This article introduces an agent-based energy management framework as a solution to enable ESSs, irrespective of their location and adherence to a microgrid, to take part in the supply–demand management of microgrids through the market-based approach.

In the proposed energy trading system, ESSs, generators, and loads of microgrids are represented by agents. The ESSs include two types of ESSs: 1) ESSs connected in a microgrid ($ESS_{Local}$) and 2) global or external ESSs not adhered to any microgrid ($ESS_{Out}$), such as community ESSs. ESS agents (both $ESS_{Local}$ and $ESS_{Out}$) interact with TE market operating agents to participate in energy trading and, thus, get integrated into the microgrids' energy management. In the proposed framework, two types of market models are presented: local storage market model and global storage market model. In the case of the local approach, external ESSs connected across the system are encouraged to participate in the internal energy management of microgrids. In this way, ESSs will be given more opportunities to trade energy service irrespective of their location and adherence. Alternatively, using the global approach, all the microgrids form a pool to reinforce the microgrid-level energy management using the energy imbalances of fellow microgrids and energy service offered by all the ESSs on the network, i.e., both $ESS_{Local}$ and $ESS_{Out}$. The concept was initially presented in [1] and further developed as a fully scalable trading platform, as presented in this article. The significant novelty of the work presented in this article is centered to the smart-bidding strategies of ESSs agents and attributing marginal distribution network losses to the corresponding transactions to make the trading fair and transparent. In addition, a fairly large case study system, compared to the system presented in [1], is presented. The main contributions of this article are given as follows.

1) Two energy storage market models are proposed to promote ESS (both $ESS_{Local}$ and $ESS_{Out}$) participation in decentralized energy trading in the interconnected microgrid environment. These market models motivate ESSs to participate either in local energy markets at the intramicrogrid level or global energy market at the intermicrogrid level.
2) Detailed modeling of the rational bidding behavior of the storage owners is presented. Also, a reinforcement learning algorithm, known as SAQL algorithm, based bidding strategy for ESSs to make their participation in the TE markets profitable is presented.
3) A complex current-tracing-based loss estimation mechanism to quantify the marginal change in network losses caused by TE transactions between ESSs and microgrids is presented.

The rest of this article is organized as follows. The proposed agent-based energy trading platform for ESSs and its different markets models are presented in Section II. Section III details the proposed auction-based electricity markets, modeling of the rational bidding behaviors of the market players, the SAQL-based bidding algorithm, and the market settlement mechanism with marginal network losses. Section IV presents the case study system and simulation results with necessary analysis. Finally, Section V concludes this article.

## II. Proposed Energy Trading Platform for Market Integration of ESSs

Fig. 1 shows the architectures of the proposed energy trading platform for storage systems and the class of agents attached to each level. It consists of the agents, viz., GenAs to represent DGs, LoadAs to represent loads, StrAs to represent ESSs and UA for the utility grid. The overall framework is built into

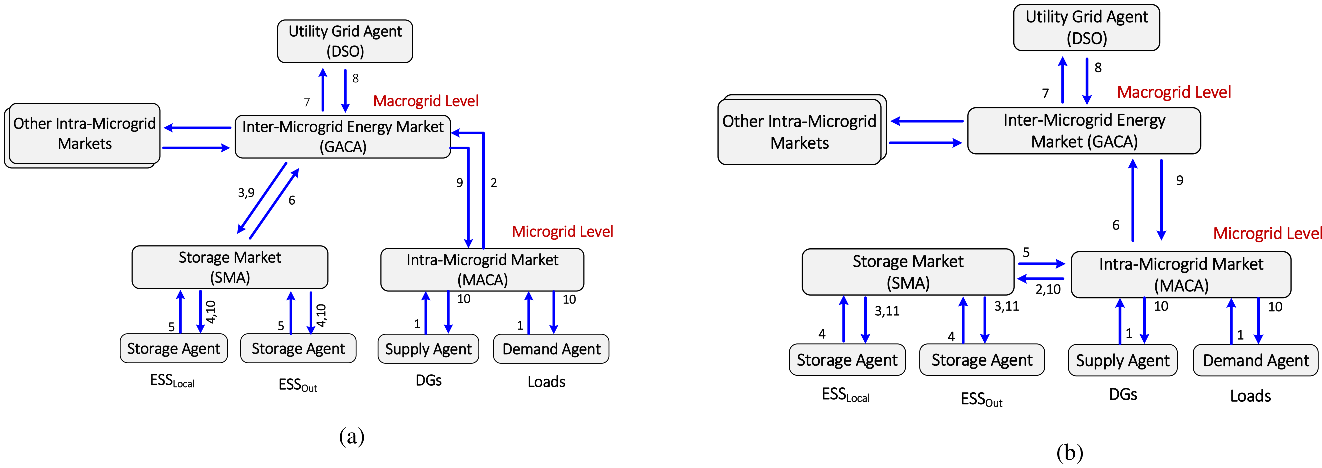



Fig. 1. Proposed agent-based energy market framework for integrating ESSs into a multimicrogrid scenario. (a) Global storage market. (b) Local storage market.

three levels: local microgrid market, storage market, and global energy market, with each level interacting with other levels in the framework for market organization. The numbers shown next to the communication links in Fig. 1 represent the sequence of data exchanges, i.e., the order in which the agents communicate to organize the markets.

*Intramicrogrid market:* This is an energy market within the microgrid, where both DGs and loads participate. It is administered by an agent called MACA, which acts as an auctioneer. It follows the CDA mechanism to clear the market in each DI, and any mismatch in power is passed to subsequent levels for clearance.

*Storage market:* In this level, an agent called SMA administers the market among the available StrAs in its mandate. The SMA issues set points to all StrAs either to $charge$ or $discharge$ or $at\ \ idle$ for the current DI based on the market outcome. The market clearing mechanism followed by the SMA is detailed in Section III-A. In addition, the SMA provides a prediction on market clearing price to the StrAs, which helps them build an optimal bidding strategy.

*Intermicrogrid market:* In this level, an agent called GACA is responsible for administering the market among the interconnected microgrids. In brief, it conducts auction among MACAs and the SMA in the network to balance the mismatches in microgrids centrally, which cannot be dealt with locally.

Besides the threefold architecture of the framework, it is highly flexible that market levels can be rearranged as required by the market operator to create more robust models by following certain rules: 1) GenAs and LoadAs must be connected to a single level and 2) intermicrogrid energy market level can interact with all intramicrogrid market levels only after the local markets are cleared. Using these rules, two different market models, viz., *global storage market* and *local storage market* models, are proposed by rearranging the storage market level. Fig. 1(a) and (b) shows the proposed market models along with the sequence of communications among the agents in both models.

In the global storage market model, all the microgrid-level markets are connected to the intermicrogrid market via the agents, MACA and GACA. The SMA of the storage market communicates with StrAs and GACA, and it takes control of all StrAs in the network, i.e., both internal ($\mathrm{ESS_{Local}}$) and external ($\mathrm{ESS_{Out}}$) storage systems. SMA delivers the $charge$ or $discharge$ or $at\ \ idle$ signal to these StrAs based on the market outcome.

In the case of the local storage market model, the market is organized locally in each microgrid by the SMA; thus, every microgrid has a storage market. In each microgrid storage market, the auction is conducted by the $\mathrm{MSMA}_i$ among the internal storages and the external ESSs, which are willing to participate. An external storage StrA can participate in $n$ local storage markets ($n \leq m$), where $m$ is the number of microgrids in the system. For example, if an external storage with rated capacity $C$ participates in $n$ local storage markets with capacities of $C_1$, $C_2$, $C_3$... and $C_n$, respectively, then $\sum_{k=1}^{n} C_k \leq C$.

## A. Global Storage Market

Fig. 1(a) shows the architectures of the global storage market. Following are the steps involved in execution of the proposed global storage market model for one DI.

*Step 1:* At the beginning of each DI, all GenAs and LoadAs of the $i$th microgrid send the generation and demand forecast together with bids to $\mathrm{MACA}_i$. Microgrid-level energy auction (intramicrogrid energy market) is conducted by $\mathrm{MACA}_i$, and the mismatch ($\Delta P_i$) is identified. MACAs communicate the nonzero $\Delta P_i$ along with the corresponding bids to the intermicrogrid level market organized by the GACA for further clearance. In the case of the local storage market model, this information is passed to the MSMA of the microgrid.

*Step 2:* The GACA conducts energy auction among all the microgrids. In this auction, $\mathrm{MACA}_i$ participates as a seller if $\Delta P_i > 0$, and buyer otherwise. The GACA generates global energy mismatch ($\Delta P$) information after the auction. For a nonzero $\Delta P$ value, the GACA invites the SMA to support by sharing the $\Delta P$ information.

*Step 3:* The SMA invites all StrAs by specifying the type of $\Delta P$ (surplus or deficit). StrAs submit bids with unit cost of energy and available capacity to $charge$ or $discharge$. The SMA conducts GSPA and identifies the optimal set of ESSs to minimize $\Delta P$ along with the unserved mismatch. This mismatch will be communicated back to the GACA.

*Step 4:* For a nonzero mismatch, the GACA requests the support from the UA, which supplies the deficit power at grid selling price ($\pi_{\text{gs}}$) and buys the surplus power at grid buying price ($\pi_{\text{gb}}$). The market outcome for each microgrid's mismatch is sent to the corresponding MACA.

*Step 5:* Every MACA compiles the final market clearing price for each GenA and LoadA and provides them the final set points and the selling/buying price of electricity.

### *B. Local Storage Market*

Fig. 1(b) shows the architectures of the local storage market. The execution of this market framework is similar to the global storage market except Steps 2 and 3, which are as follows.

*Step 2:* $\text{MSMA}_i$ issues auction call to all StrAs (both internal and external ESSs) specifying only the type of mismatch (surplus or deficit). All StrAs submit the bids that include unit price of energy and available potential for $charging$ or $discharging$, and the GSPA auction will be conducted by $\text{MSMA}_i$, where it identifies the optimal set of ESSs' bids to minimize $\Delta P_i$ and computes the unserved mismatch after market clearance ($\Delta P^r$). This will be communicated back to $\text{MACA}_i$ along with the optimal set of ESSs bids.

*Step 3:* For nonzero mismatch, $\text{MACA}_i$ participates in global market organized by the GACA. Every $\text{MACA}_i$ enrolls in the global market either as a seller if $\Delta P^r > 0$ or a buyer otherwise. The GACA organizes the CDA market among the microgrids and declares the energy contracts among the microgrids and computes the final energy mismatch ($\Delta P$).

At this point, it is worthy to highlight that the global storage market model facilitates storage owners connected anywhere in the system (inside or outside a microgrid) to charge or discharge for overall mismatch in the multimicrogrid system, irrespective of their location in the system, and thus attracts more private players to invest in storage setup installations. On the other hand, the local storage market model allows external storage systems with a choice to participate in any of the local microgrid markets, thereby increasing the opportunity for them to gain more profit.

## III. Energy Market Mechanisms

In this section, the market clearance mechanism adopted by the proposed set of market models, bidding strategy designed for ESSs, and the transaction-based network loss allocation mechanism are detailed. The market mechanisms used in the proposed system are 1) the CDA mechanism, which is used in both intra- and intermicrogrid-level energy markets and 2) GSPA, which is used in storage market level.

*CDA for energy market:* Local and global energy markets organize a subhourly (15 min) energy auction using the CDA algorithm. It is a popular and widely used electricity market mechanism, in which sellers submit their quotes (known as asks) and buyers submit their quotes (known as bids) to the market operators, which, in turn, declare the clearance of the market if the lowest ask is greater than or equal to the highest bid in the current market round, and the clearing price is the average of these two prices. Therefore, it ensures least-cost dispatch of the demand through auction.

*Generalised Second Price Auction (GSPA) for storage market:* It is a type of electricity auction, where all the bidders quote bids (sealed) simultaneously for a commodity (electricity) or an opportunity to serve the load. Like the other forms of auctions, GSPA identifies the winners based on prices quoted. The highest quoted bidder is the $\text{Winner}_1$ to gain the chance to acquire the item (say a quantum of energy) at a price quoted by the next highest bidder, say $\text{Winner}_2$. If the availability of the item is more than the requirement of $\text{Winner}_1$, then $\text{Winner}_2$ is selected and asked to pay the price quoted by $\text{Winner}_3$, and so on. It is to be noted that GSPA is an extension of the popular Vickrey's second price auction mechanism. Also, in GSPA bidding, one's true value is the dominant winning strategy [19].

### *A. Modeling of StrAs Bidding Behavior*

In the proposed system, the market participation behavior of the StrAs is modeled in terms of eagerness to import or export the energy depending on the present SOC. Thus, the eagerness of the $i$th storage system to charge or discharge at time $t$, represented as $\phi_C^i(t)$ or $\phi_D^i(t)$, respectively, can be modeled as a function of the SOC and safe operating limits of the ESS as follows:

$$\phi_C^i(t) = \left[\frac{k_i}{1 - \text{SC}_t^i}\right] \text{ and } \phi_D^i(t) = \left[\frac{k_i}{\text{SC}_t^i}\right] \tag{1}$$

$$\text{SC}_i(t) = \frac{\text{SOC}_i^{\max} - \text{SOC}_i(i)}{\text{SOC}_i^{\max} - \text{SOC}_i^{\min}} \tag{2}$$

where $k_i$ is a modeling parameter (private value) defined by the owner of the $i$th storage system, $\text{SC}_i(t)$ is the capacity factor for the $i$th storage system in interval $t$, and $\text{SOC}_i^{\text{rated}}$ and $\text{SOC}_i^{\min}$ are the maximum and minimum permissible ratings of the $i$th ESS in kilowatthour, respectively. $\text{SOC}_i^{\min}$ is decided by the owner of storage taking the life of the ESS into consideration. The participation of the ESS in auction markets shall generate revenue for each charge–discharge cycle it undergoes, and the profit will be generated if the charging bid is less than the overall discharge bid. This connotes that ESSs quote higher price for the energy than the equivalent unit cost of energy accumulated through charging. The charging ($\text{CBid}_i(t)$) and discharging ($\text{DBid}_i(t)$) bids of the $i$th storage system in interval "$t$" are calculated as

$$\text{CBid}_i(t) = \text{CBE}_i(t) - \phi_C^i(t) \cdot \alpha_i^c(t) \tag{3}$$

$$\text{DBid}_i(t) = \text{CBE}_i(t) + \phi_D^i \cdot \alpha_i^d(t) + \Lambda_i(t) \tag{4}$$

where $\text{CBE}_i(t)$ is the cost of banked energy of the $i$th storage expressed in cents per kilowatthour. $\alpha_i^c(t)$ and $\alpha_i^d(t)$ are the hyperparameters chosen by the StrAs based on their experience and profit motivation. $\Lambda_i(t)$ represents the component of battery life degradation cost, which depends on the type of the battery used in the ESS. In the proposed approach, it is assumed that ESSs use Li-ion nickel cadmium aluminum type batteries, and the corresponding cycle life degradation cost per kWh of $i^{th}$ ESS at time $t$ can be modeled as given in (5) and (6), where $D_t$ is the depth of discharge in kilowatthour at the end of the interval $t$ and $P_D$ is the power in kilowatt that the ESS can supply during the interval $t$, $C_{\text{Bat}}$ is the cost of battery in dollars, and $\Delta t$ is the length of the DI in hours. $N_{D_t}$ and $N_{D_{t+1}}$ are the corresponding number of cycles of life of ESS in log-scale [20]

$$\Lambda_i(t) = \left(\frac{1}{J(D_{t+1})} - \frac{1}{J(D_t)}\right) \times C_{\text{Bat}} \tag{5}$$

$$J(D_t) = 10^{N_{D_t}} \text{ and } D_{t+1} = D_t + P_D(t) * \Delta t. \tag{6}$$

In (3) and (4), if $\alpha$ is zero, then the charging and discharging bids differ by only the degradation cost, and for $\alpha = 1$, the bids are dictated by the eagerness and *CBE*. Thus, the value of $\alpha$ decides optimum eagerness to be used to calculate the bids. It is important to note that the higher values of $\alpha$ increase the price quotes and may cause losing the auction as per the GSPA mechanism. On the other hand, submitting lower bids is not profitable to the ESS owners. In the proposed energy management framework, a reinforcement learning algorithm is proposed to assist the StrAs in calculating the optimum bid for various scenarios using the SAQL algorithm [21].

*1) SAQL-Algorithm-Based Bidding Strategy for ESSs:* The $Q$-learning algorithm belongs to the class of reinforcement algorithms, whose basis resembles the animal survival strategies in nature, i.e., continuous learning. The agents with the $Q$-learning ability can effectively use the past experience to improve their behavior strategically. Also, due to the model-free nature, it is highly preferred for online applications, such as electricity markets, to obtain an optimal decision by directly interacting with the environment. In $Q$-learning theory, agent's memory or knowledge is represented by a matrix called $Q$-matrix, which connects set of possible states of the environment, represented by $\widehat{Z} = \{z_1, z_2, \ldots, z_s\}$, to the set of actions that the agent can perform, represented by $\widehat{Y} = \{y_1, y_2, \ldots, y_a\}$. For each state ($z_i$) and action ($y_j$) pair, the agent assigns a probability ($Q(i,j)$) computed through continuous learning. This probability indicates the chance of receiving the maximum reward ($\rho$) by performing the action ($y_j$)

$$Q_{k+1}(z,y) = \begin{cases} (1-\lambda)\cdot Q_k(z,y) \\ \quad +\lambda\cdot(\rho_k + \gamma\cdot \underset{\{y\}}{\text{argmax}}\, Q_{k+1}(z_{k+1},y)) \\ \quad \text{if } z = z_k \text{ and } y = y_k \\ Q_k(z,y) \;\; \text{otherwise} \end{cases}. \tag{7}$$

For example, during a learning stage $k$ if the agent takes an action $y_k$ for the state $z_k$, then for the succeeding stages, the $Q$-update rule is given by (7), where $\lambda$ represents the learning rate and $\gamma$ represents the discount factor for the learning process. The values of these parameters are chosen from the range (0,1] with a caution that higher values of $\gamma$ motivate the agent to choose actions with high rewards in near future than in distant future.

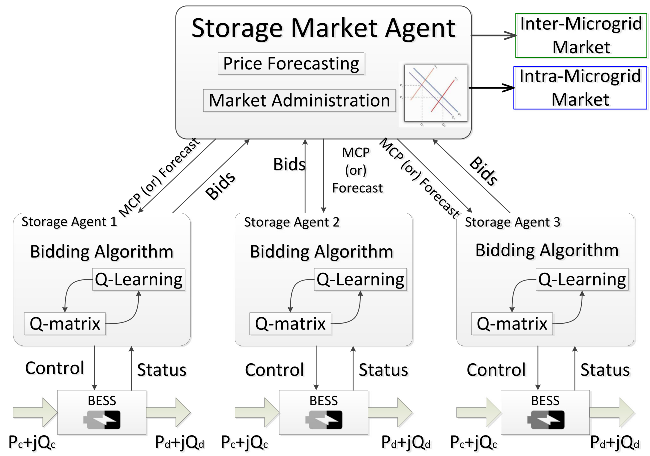



Fig. 2. Storage market architecture with StrAs following SAQL-based bidding.

In the proposed energy trading framework, StrAs built their bidding strategy using the $Q$-learning algorithm. In this scenario, the environment is market and is defined in terms of different states based on the predicted market clearing price as $\widehat{Z}_{\text{market}} = \{z_1 = \pi_{\text{gb}} + \delta, z_2 = \pi_{\text{gb}} + 2\delta, \ldots, z_s = \pi_{\text{gb}} + s\delta\}$, where $\delta$ is calculated as the ratio of the market range, i.e., $(\pi_{\text{gs}} - \pi_{\text{gb}})$, to the number of states ($s$). The StrAs determine the state of the environment as $z_i$, if the predicted market clearing price for an interval $t$ ($\pi_p(t)$), announced by the SMA, lies between $\pi_{\text{gb}} + (i-1)\delta$ and $\pi_{\text{gb}} + i\delta$. Based on the observed state, each StrA determines a suitable action, i.e., choosing a value for $\alpha_i^c(t)$ or $\alpha_i^d(t)$ to calculate the bid, which yields the highest reward in the current market round. Therefore, a set of actions is defined as $\widehat{Y}_{\text{market}} = \{y | y_i = \{(\alpha_{\max} - \alpha_{\max})/a\} * i, \; \forall\, i \in [1,a]\}$, where $a$ is the number of actions. In the case of sellers, i.e., discharging the ESSs, the reward is equal to $(\text{MCP} - \pi_{\text{gb}}) \cdot P_D \cdot \Delta T$, and in the case of buyers, i.e., charging of ESSs, it is equal to $(\pi_{\text{gs}} - \text{MCP}) \cdot P_C \cdot \Delta T$, where $P_D$ and $P_C$ are the discharging and charging powers in kilowatt, respectively, MCP is the transaction price assigned by the SMA, and $\Delta T$ is the duration of the DI in hours. Based on the chosen action, the bids will be calculated using (3) and (4). The pseudocode of the SAQL algorithm is given in Algorithm 1, and the schematic of the storage market with StrAs following the proposed bidding algorithm is shown in Fig. 2. It is important to note that the SAQL algorithm converges faster than the conventional $Q$-learning algorithm due to the randomness added by the $\epsilon$-greedy policy [21]. This connotes that the SAQL algorithm requires a significantly less number of training iterations to converge on the optimal bidding policy for the given market environment [21].

### B. Marginal Network Losses of a Transaction

Energy losses caused by transactions between ESSs and microgrids must be quantified and allocated to both ends of the transaction fairly. The losses greatly influence the profitability

**Algorithm 1:** SAQL Algorithm.

1) Initialize $Q(s \times a)$ matrix with arbitrary values
2) **For each training stage** $k$,
   a) Choose an arbitrary state $z$ as initial state
   b) *For each step in the training stage*
      i) Choose an action $y^r$ randomly from the set of actions
      ii) Choose another action $y^p$ such that $y^p = \underset{y \in \widehat{Y}}{\text{argmax}}\ Q_{k-1}(z, y)$
      iii) Choose a value for $\epsilon \in (0, 1)$ and select the action $y_k$ such that

$$y_k = \begin{cases} y^r, & \text{if } \epsilon < \exp\left(\frac{(Q_{(k-1)}(z,y^r) - Q_{(k-1)}(z,y^p))}{T_k}\right) \\ y^p, & \text{otherwise} \end{cases}$$

      iv) Implement action $y_k$, receive the reward $\rho_k$, and observe the next state $z'$
      v) Update the $Q$-matrix using the rule given in (7)
      vi) $z \leftarrow z'$
      *Until the desired state is* $z$
   c) Recalculate $T$ as $T_{(k+1)} = \theta \times T_k$, where $\theta \in (0.5, 1)$

**Until the maximum number of training stages has been analyzed.**

of a transaction, as the cost of incremental losses must be paid to the utility. In the proposed framework, a current-tracing-based loss allocation mechanism is used to quantify the marginal losses caused by each transaction. The method requires power flows on the system, which are available only after the execution of the transaction. However, to approve a new transaction, its marginal loss contribution needs to be known *a priori*. Therefore, after clearing the market, the GACA submits the list of possible transactions to the UA, which evaluates the effect of the set of transactions on the overall system loss and allocates the marginal loss to each transaction. At this stage, the UA uses the most recent power flows recorded on the system superimposed with the additional flows caused by the transactions announced by the GACA and the forecasted load change in the overall system. The allocated losses together with the transaction details are sent to the corresponding ESSs and microgrids via the SMA and the GACA to assess the economic feasibility. The marginal loss component of each transaction is estimated by the UA using the following mechanism.

Let $\hat{I}_k = I_k^p + jI_k^q$ be the most recently measured complex current flow in a line $k$ connected between nodes $n_1$ and $n_2$. Let $L_k$ be the power loss in line $k$, which is proportional to $|\hat{I}_k|^2$. Using the proportional sharing principle, the current contribution of each nodal injection in the system to the flow of current in the line $k$ can be traced [22]. Let $\hat{I}_{k,m} = I_{k,m}^p + jI_{k,m}^q$ be the contribution of a nodal injection at bus $m$ to the line current $\hat{I}_k$. If $H$ sets all nodes that contribute to the flow on line $k$, then

$$I_k^p + jI_k^q = \left(\sum_{m \in H} I_{k,m}^p\right) + \left(\sum_{m \in H} I_{k,m}^q\right). \tag{8}$$

Let $L_{k,m}$ be the portion of losses on the line $k$ assigned to the nodal injection at bus $m$. It can be expressed as

$$L_{k,m} = \left((I_{k,m}^p)^2 + (I_{k,m}^q)^2 + U_{k,m}\right) \times r_k \tag{9}$$

where $r_k$ is the resistance of the line $k$ and $U_{k,m}$ is a function representing the contribution of cross terms

$$U_{k,m} = \beta_{k,m}^p \cdot I_{k,m}^p \sum_{i \in H, i \neq m} I_{k,i}^p + \beta_{k,m}^q \cdot I_{k,m}^q \sum_{i \in H, i \neq m} I_{k,i}^q \tag{10}$$

$$\beta_{k,m}^p = \frac{2 \cdot (I_{k,m}^p)^2}{(I_{k,m}^p)^2 + (I_{k,m}^q)^2}, \quad \beta_{k,m}^q = \frac{2 \cdot (I_{k,m}^q)^2}{(I_{k,m}^p)^2 + (I_{k,m}^q)^2}. \tag{11}$$

Also, $\beta_{k,m}^q + \beta_{k,m}^p = 2$. It is important to note that the above procedure is using the most recent measurements taken on the system. In order to find the effect of the new set of transactions, the UA has to estimate the changes in each line flow caused by the transactions and usual load change across the system. The system load change can be identified using the forecasted demand curve. The effect of the estimated load change together with the market-based energy transactions can be found by using the PTDF approach [23], as shown in the following.

If a transaction is set to occur between the nodes $s$ and $d$, then the change in current flowing through the line $k$ can be approximated using the PTDF as

$$\Delta I_k^{s,d} \approx \text{PTDF}_{s \to d,k} \times \left(\frac{S_{s,d}}{V_l}\right)^* \tag{12}$$

where $\Delta I_k^{s,d}$ is the change in current flow in the line $k$ due to the scheduled transaction between nodes $s$ and $d$, $S_{s,d} = p_{s,d} + j \cdot q_{s,d}$ is the volume of power transferred between the nodes $s$ and $d$, $V_l$ is the voltage at node $l$, and $\text{PTDF}_{s \to d,k}$ is the PTDF of the line $k$ for the transaction between the nodes $s$ and $d$. It is a constant value calculated using the line reactances [23]. In addition to the energy transactions, the system load variation also alters the line flows. The UA can predict the load variation using the forecasted daily load curve of the system. This load variation can be modeled as a group of transactions between each load on the system and the utility, and their impact on line flows can also be analyzed using the PTDF approach given in (12). Therefore, the overall effect of both market-based transactions and load variation on each line in the system can be found as

$$\hat{I}_k^{\text{new}} = I_k^p + jI_k^q \approx \hat{I}_k^{\text{old}} + \sum_{(s,d) \in G} \Delta I_k^{(s,d)} \tag{13}$$

where $G$ is the set of both market-based and load-variation-based transactions. The new flows will be used to calculate the losses in each line and the portion of loss allocated to the node $s$ using

$$P_{\text{Loss}}(s) = \sum_{k \in \text{All lines}} L_{k,s}. \tag{14}$$

Using $P_{\text{Loss}}(s)$, the losses caused by a transaction between the nodes $s$ and $d$ can determined as

$$P\text{Loss}_{(s \to d)} = P_{\text{Loss}}(s) * \frac{p_{s,d}}{p_s} \tag{15}$$

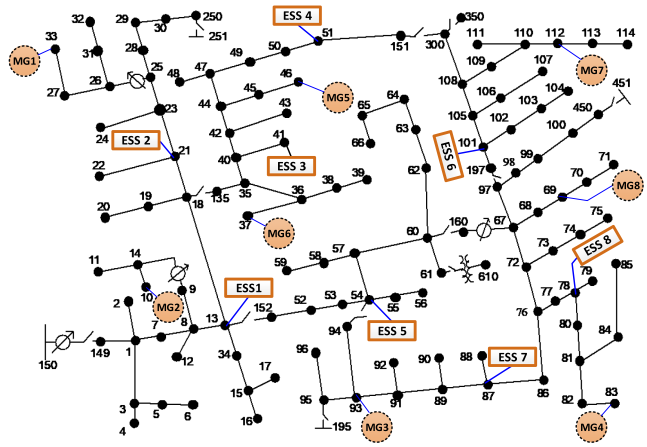



Fig. 3. 123-node distribution network with eight microgrids and ESSs.

where $p_s$ is the total power injection at node $s$ in kilowatt. The losses assigned to each transaction are then informed to the corresponding ESSs and microgrids. In the proposed framework, it is assumed that the energy required to compensate the losses are supplied by the utility at $\pi_{\text{gs}}$, and each trader verifies the economic feasibility of the transaction based on the cost of losses assigned using this price.

## IV. Case Study

The proposed energy trading system for ESSs is applied to a modified IEEE 123-node distribution network with eight microgrids and eight external storage systems ($\text{ESS}_{\text{out}}$), as shown in Fig. 3. The locations of microgrids are chosen as per the data provided in [24], whereas the locations of ESSs are chosen to have at least one ESS per each section of the system. The sections can be formed using tie-line switches available in the system. The tie-line switches connecting different sections, i.e., nodes 13 to 152, 18 to 135, 54 to 94, and 97 to 197, are considered as normally closed to maintain the radial structure of the network. Each microgrid is modeled as a combination of two DGs (wind based), two loads, and an internal ESS ($\text{ESS}_{\text{Local}}$). The ratings of DGs in each microgrid are chosen as 150 and 200 kW, and the forecast of their power generation is taken from [14]. The forecast for power consumption of loads is chosen such that the overall power mismatches in the microgrids are as shown in Fig. 4. The overall system is simulated using OpenDSS, and the proposed agent system is implemented on the JADE framework and connected to OpenDSS using *com4j* package.

The ratings of the ESSs (both $\text{ESS}_{\text{Local}}$ and $\text{ESS}_{\text{Out}}$) are provided in Table I. The initial SOCs of all ESSs are chosen from the range $[\text{SOC}^{\text{min}}, \text{SOC}^{\text{max}}]$. Also, the length of DI is chosen as 15 min; thus, a day contains 96 intervals. The value of $\pi_{\text{gs}}$ is chosen as 13.5 ¢/kWh, whereas the buying price, $\pi_{\text{gb}}$, is chosen as 9 ¢/kWh, which is the feed in tariff of the grid [25]. The DGs and loads of each microgrid submit the forecast of generation and demand, respectively, for the immediate next interval with the corresponding bids to the MACA of the microgrid. The MACA clears the market using the least-cost dispatch mechanism, i.e., the CDA. The mismatches that cannot be balanced locally are

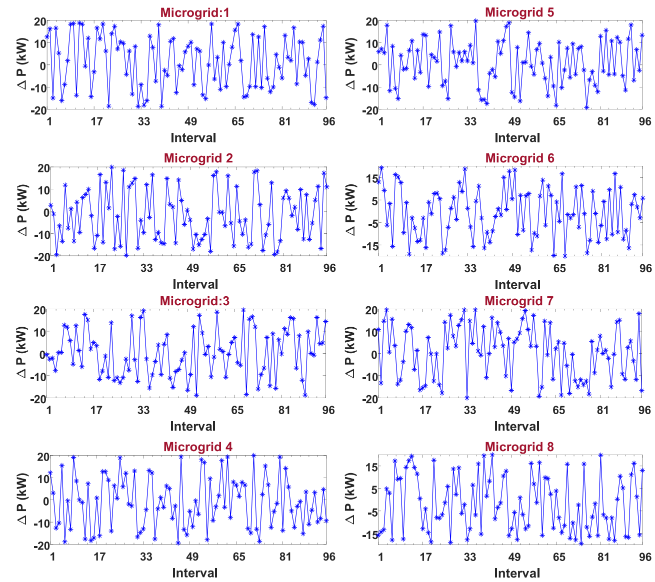



Fig. 4. Forecast of power mismatches in the microgrids in kilowatt.

TABLE I
Ratings of ESSs in the System

| Parameter | $ESS_{Local}$ | $ESS_{Out}$ |
|---|---|---|
| Rated $SOC$ in kWh | 30 | 60 |
| Rated kW | 10 | 20 |
| $SOC^{min}$ | 10% | 10% |
| $SOC^{max}$ | 100% | 100% |
| Maximum $DOD$ | 0.85 | 0.85 |
| CBE (¢/kWh) | $\in [11, 12]$ | $\in [11, 12]$ |
| Cycle Life | 600 at Max. DOD | 800 at Max. DOD |

the prime focus of the proposed trading mechanism. These mismatches are managed using the local storage market approach within the microgrid or by following the global storage market approach among the microgrids.

The price forecast model followed by the SMA is taken as $c_0 + c_1 \times (\Delta P)$, where $c_0$ is taken as 11.25 ¢/kWh and $c_1$ as $-0.042$ ¢/$(\text{kW}^2 \cdot \text{h})$ [26]. The price forecast model is designed based on the market price range, $[\pi_{\text{gb}}, \pi_{\text{gs}}]$, such that under the zero-mismatch condition, the market clears at the average of the price range. Upon requested by the SMA, StrAs participate in the storage market by submitting the bids calculated using the SAQL algorithm given in Section III-A. For this, the market is defined in terms of 20 states, and the number of actions of the agents (choosing a value of $\alpha_c$ or $\alpha_d$) is chosen as 25. The modeling parameters used by StrAs are taken as follows. The learning rate $\lambda$ for ESS-1, ESS-3, ESS-6, and ESS-7 is chosen from the uniformly distributed range of values $U[0.8, 0.9]$, whereas for other external ESSs, it is chosen from the range $U[0.6, 0.8]$ to distinguish the traders based on their learning ability. Also, the learning rate for internal ESSs is chosen as zero, which indicates that they have no learning ability. Using the above parameters, the StrAs are allowed to learn the bidding strategies of the competitors using the SAQL algorithm from the market trial runs. For the presented system, a total of 537 market trail runs for the local market approach and 412 trial runs for the

TABLE II
PROFITS OF THE ESSs FROM LOCAL STORAGE MARKETS

| MG\ESS | Profit Earned by ESSs in the system in ($) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $ESS_{Local}$ | ESS 1 | ESS 2 | ESS 3 | ESS 4 | ESS 5 | ESS 6 | ESS 7 | ESS 8 |
| MG1 | 9.963 | 0.0 | 37.4 | 55.09 | 0 | 0 | 0 | 0 | 0 |
| MG2 | 5.78 | 52.7 | 38.0 | 0.00 | 0 | 0 | 0 | 0 | 0 |
| MG3 | 10.407 | 0 | 0 | 0 | 0 | 41.8 | 0.0 | 51.4 | 0.0 |
| MG4 | 6.9 | 0 | 0 | 0 | 0 | 0.0 | 0.0 | 46.5 | 37.2 |
| MG5 | 7.89 | 0 | 0 | 54.9 | 39.7 | 0.0 | 0.0 | 0.0 | 0.0 |
| MG6 | 8.61 | 0 | 0 | 0.0 | 41.9 | 0.0 | 42.4 | 0.0 | 0.0 |
| MG7 | 7.77 | 0 | 0 | 0.0 | 0.0 | 29.5 | 46.9 | 0.0 | 0.0 |
| MG8 | 10.452 | 33.3 | 0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 32.4 |
| Total Profit ($) | | 86.0 | 75.4 | 110.0 | 81.6 | 71.3 | 89.3 | 97.9 | 69.6 |
| Cost of Energy Losses ($) | | 4.1 | 2.3 | 3.3 | 2.5 | 3.5 | 3.8 | 2.5 | 1.9 |
| Net Profit ($) | | 81.9 | 73.1 | 106.7 | 79.1 | 67.7 | 85.5 | 95.4 | 67.7 |

global approach were conducted to allow the StrAs to converge on achieving the $Q$-matrix that reflect their rational bidding behavior. After the training episode, the agents are set to bid in the storage markets using the case study data presented in earlier part of this section.

### A. Local Storage Market Approach

Under this approach, the energy mismatches in microgrids are managed using internal ESSs of the microgrids and the $\mathrm{ESS}_{\mathrm{Out}}$ that have agreed with the microgrids to support the local energy balancing. In this case study, it is assumed that each external ESS participates in two different microgrids with 50% of its capacity, i.e., each 20-kW (60-kWh capacity) $\mathrm{ESS}_{\mathrm{Out}}$ participates in two distinct local storage markets of microgrids as a substorage with 10-kW (30-kWh capacity) rating. For example, if the first substorage of an ESS got a contract to deliver 7 kW (discharge) to one microgrid, while the second one got a contract to consume 5 kW (charge) from another microgrid, then the actual power delivered by the ESS is only 2 kW.

In each DI, based on the supply–demand mismatch in the microgrids, both internal and external ESSs (referred as local traders) participate in the market. Table II shows the association of external ESSs with the microgrids in the system. For example, ESS1 participates in the local energy balancing of MG2 and MG8 and, thus, has a nonzero profit values in the corresponding rows of these microgrids. In any interval, local traders submit the bids based on the price forecast and mismatch information of the subsequent interval provided by the SMA. As described in Section II-B, the SMA follows the second price auction to decide the winners and balances the mismatch based on the auction outcome.

For example, Fig. 5(a) shows a comparison between the mismatches in MG1 before and after organizing the local energy storage market. The mismatches that cannot be minimized further using ESSs are balanced by the utility grid at $\pi_{\mathrm{gs}}$ or $\pi_{\mathrm{gb}}$ depending on the volume of mismatch. But, in the case of MG1, the mismatches are balanced by local traders without the support of the utility grid; thus, the postmismatches are zero, as shown in Fig. 5(a). Fig. 5(b)–(d) shows the schedule of substorages of ESS3, ESS2, and $\mathrm{ESS}_{\mathrm{Local}}$ of MG1, respectively, identified by the SMA using the auction algorithm. From the figure, it can be observed that the external ESSs, i.e., the substorages of ESS3 and ESS2, are preferred over the $\mathrm{ESS}_{\mathrm{Local}}$ to balance the mismatches

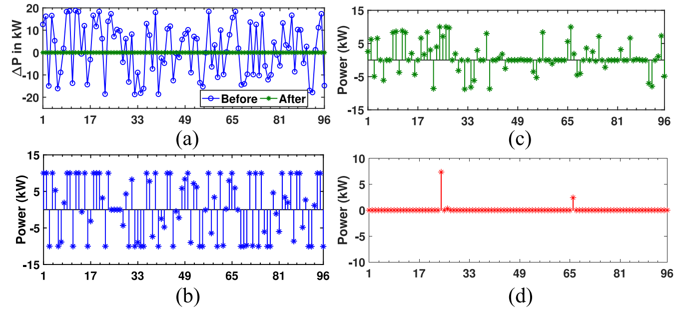



Fig. 5. (a) Power mismatches in MG1. Charging and discharging schedules of substorages of (b) ESS3, (c) ESS2, and (d) $\mathrm{ESS}_{\mathrm{Local}}$ of MG1.

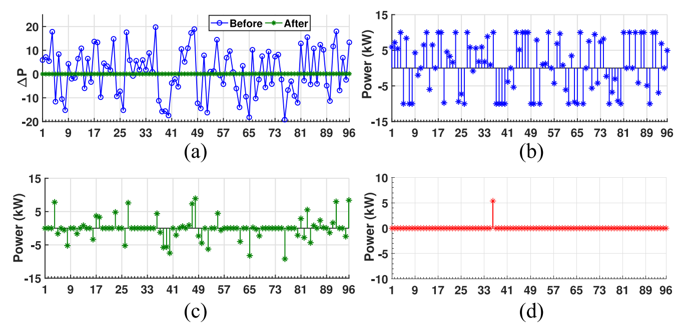



Fig. 6. (a) Power mismatches in MG5. Charging and discharging schedules of substorages of (b) ESS3, (c) ESS4, and (d) $\mathrm{ESS}_{\mathrm{Local}}$ of MG5.

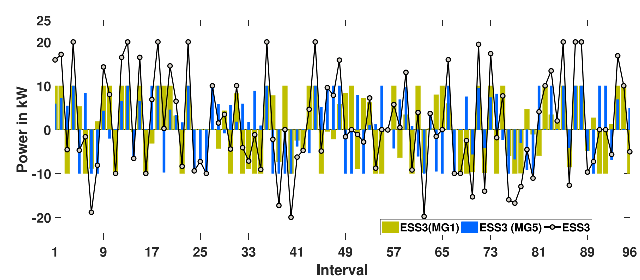



Fig. 7. Charging and discharging schedules of ESS3 and its substorages.

in MG1. This is because the bids placed by ESS3 and ESS2 have undercut the bids of $\mathrm{ESS}_{\mathrm{Local}}$ due to their higher learning rates. Fig. 6 shows the power imbalances of MG3 and charging and discharging schedules of associated ESSs. Similar to MG1, the external storage systems have outperformed the local storage system ($\mathrm{ESS}_{\mathrm{Local}}$ of MG5). Also, it can be observed that the bids placed by ESS3 had undercut the bids of ESS4 due to the high learning rate of ESS3. From Figs. 5 and 6, the actual schedule of ESS3 can be obtained by aggregating the schedules of its substorages, as shown in Fig. 7.

Fig. 8 shows the power imbalances of MG3, and charging and discharging schedules of associated ESSs. From the figure, it can be observed that the power imbalances are not completely suppressed by the ESSs, as all the three ESSs have no sufficient power for discharging during the interval 52. Therefore, MG3 purchased the required power from the intermicrogrid market to satisfy the demand.

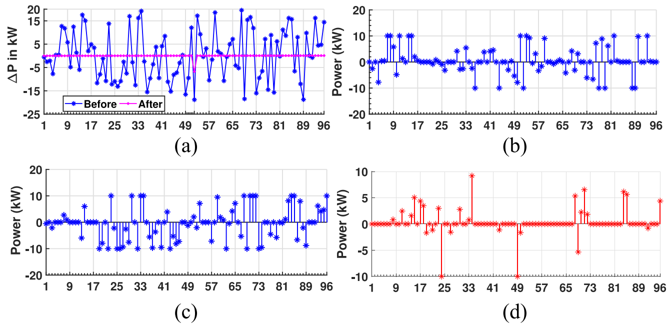



Fig. 8. (a) Power mismatches in MG3. Charging and discharging schedules of substorages of (b) ESS5, (c) ESS7, and (d) $\text{ESS}_{\text{Local}}$ of MG3.

The market simulation is repeated using the monthly data obtained by adding $\pm 10\%$ variation to the data presented in Fig. 4. Table II presents the monthly overall profit obtained by ESSs by participating in local storage markets of the microgrids. Based on the comparison, it can be understood that ESSs that follow the SAQL algorithm to bid in the market certainly gain higher profits than the ESSs with no learning, i.e., $\text{ESS}_{\text{Local}}$. Also, ESSs with higher learning rate, i.e., ESS1, ESS3, ESS6, and ESS7, have gained relatively more profit than the ESSs with less learning rate, i.e., ESS2, ESS4, ESS5, and ESS8. For example, ESS3 gained a profit of \$106.7, whereas ESS2 obtained \$73.1 only.

The net profit values given in Table II are calculated by subtracting the total cost of network losses allocated to each ESS from the profit gained by the ESSs. The losses and corresponding cost are calculated by assuming that the losses on the system are balanced by the utility grid at $\pi_{\text{gs}}$, as described in Section III-B. The total cost of losses allocated to ESSs in a month is indicated in Table II. It is important to note that the losses allocated to an ESS is the sum of losses allocated to all the transactions between the ESS and the microgrids.

## *B. Global Storage Market Approach*

Unlike the local approach, in this case, the supply–demand mismatches in microgrids are balanced in a pool-based market, and all the ESSs in the system, including the internal storages of microgrids, are utilized to balance the overall mismatch in the pool. The MACA of each microgrid forwards the mismatches to the GACA along with bids and offers for each interval. In this approach, the energy trading among the microgrids happened first using the CDA mechanism, and the net mismatch that cannot be balanced by the microgrids is then announced to the SMA. The StrAs of all ESSs submitted bids to the SMA based on the amount of mismatch by following the SAQL algorithm described in Section III-A1. The simulation is carried out using the month data as described in the local approach. Table III presents the overall profit gained by ESSs and the cost of losses allocated to ESSs. From the simulation results, it can be observed that the bids of the ESSs with higher learning rate have outperformed the energy trading strategies of ESSs without or less learning rate.

TABLE III
PROFITS OF THE ESSs FROM GLOBAL STORAGE MARKETS

| Index | Pofit Earned (\$) | | Net Profit after Losses (\$) | |
|---|---|---|---|---|
| | $ESS_{Local}$ | $ESS_{Out}$ | $ESS_{Local}$ | $ESS_{Out}$ |
| **1** | 3.60 | 51.50 | 3.51 | 50.83 |
| **2** | 6.90 | 20.35 | 6.64 | 19.35 |
| **3** | 6.93 | 54.98 | 6.72 | 53.20 |
| **4** | 3.30 | 27.21 | 3.21 | 26.21 |
| **5** | 4.97 | 23.75 | 4.76 | 22.82 |
| **6** | 2.70 | 49.77 | 2.62 | 49.01 |
| **7** | 3.38 | 52.64 | 3.31 | 50.22 |
| **8** | 4.70 | 23.20 | 4.63 | 22.10 |

Similar to the local storage market simulation, the net profit gained by ESSs indicated in Table III shows the profit after subtracting the cost of power loss allocated to ESSs. For the case study system taken, the mismatch in all the microgrids after the global storage market is zero. This is due to 1) the diverse nature of the load consumption in the microgrids causing the aggregated mismatch in the pool significantly diminish and b) the aggregated capacity of ESSs is strong enough to address the mismatches in the pool. However, this may not always be the case in practical scenarios, where the aggregated mismatch can be beyond the capacity of ESSs. In such cases, it will be balanced by the utility grid. Unlike the previous market model, in this approach, the $\text{ESS}_{\text{Local}}$ of a microgrid can trade its service to other microgrids to address their mismatches in those microgrids. Thus, losses are also allocated to the internal ESSs, as shown in Table III.

## *C. Discussion*

By comparing the profits earned by ESSs in two approaches (see Tables II and III), it can be observed that ESSs were used more often in energy management of microgrids in the local storage market model than in the global approach. In the former case, ESSs located close to the microgrids will be preferred over the distant ESSs. This is because, in a radial network, the losses caused by a transactions between the microgrids and the nearest ESSs is less compared to the transactions between MGs and remote ESSs. For example, in Table II, the profit earned ESS1 from the local storage market of MG8 is less compared to the profit earned from MG2 due the losses allocated to the transactions between MG8 and ESS1. However, if the cost of losses assigned to the transaction are in the acceptable limits to both parties of the transaction, then ESSs located at any node of the system can participate in local storage market of any microgrid. In this way, the local approach provides more opportunities for ESSs to trade energy and earn profit, which eventually promotes large-scale deployment of ESSs in distribution grids.

On the other hand, the global approach reduces the burden on ESSs, as the mismatches in the microgrids are aggregated in the pool. However, ESSs were used to balance the overall mismatches after aggregation. It is also important to observe that the installed capacity of ESSs is not fully utilized, indicating that a smaller capacity of the ESSs is sufficient compared to the local approach to balance the mismatches in microgrids using this approach. Moreover, the global approach extends the scope of internal storage systems of a microgrid to other microgrids in

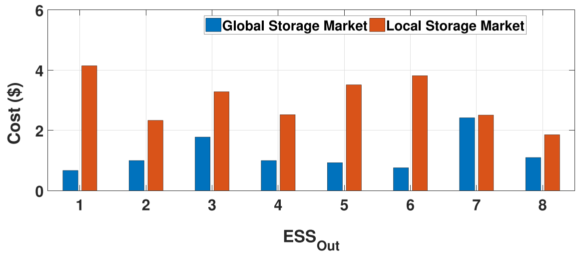



Fig. 9. Comparison of the cost of network losses attributed to ESSs.

the system. It is to be noted that the changes in the energy mix or consumer behaviors/load types cause the power imbalances to be addressed by the ESSs change, which eventually changes the price of electricity in both intra- and intermicrogrid markets. The new prices motivate StrAs to reconstruct the optimal bidding policies as per the proposed bidding strategy.

Fig. 9 presents a comparison among the cost of network losses attributed to the ESSs in both the approaches. As shown in the Fig. 9, the losses assigned to ESS1 in the local approach are higher than rest of the ESSs. This is because ESS1 participates in the local storage market of MG8, which is electrically far from ESS1. Similarly, ESS6 also has high share of losses due to its participation in the local markets of MG6. In Fig. 9, the cost of losses paid by ESSs in the global storage market is relatively small compared to the local approach. This is because the bids of ESSs located close to the microgrids have undercut the bids of the ESSs located far from the microgrids.

## V. Conclusion

This article presents an agent-based flexible energy trading framework to reinforce the energy management in interconnected microgrid systems by strategically integrating both external and internal ESSs into the trading. The framework suggests two market models: global and local storage markets. The former model forms a spot market for microgrids to transact the energy imbalances with each other and then allows ESSs connected anywhere in the system to trade their services to minimize the aggregated mismatch.

On the other hand, the local storage market approach manages the energy mismatches in microgrids locally by allowing some of the external storages to trade their services in the internal spot market. Hence, external ESSs connected across the system can transact in multiple spot markets with their desired capacity not exceeding the rated capacity. However, the location of storage plays an important role in cost dynamics of ESSs due to losses accompanied during the transfer of power between the ESSs and microgrids in a real lossy network. The proposed SAQL-based bidding algorithm allows the ESSs owners to outperform the competitors by learning their bidding strategies. The proposed model is implemented on a 123-bus distribution system with multiple microgrids and community-based ESSs. The market simulation results proved that the proposed energy trading platform and the bidding algorithm can make the integration of ESSs into a multimicrogrid system viable and promote the large-scale deployment of ESSs in distribution systems.

## References


[1] A. Sesetti, H. S. V. S. K. Nunna, S. Doolla, and A. K. Rathore, "Multi-agent based energy trading platform for energy storage systems in distribution systems with inter-connected microgrids," in *Proc. IEEE Ind. Appl. Soc. Annu. Meeting*, Sep. 2018, pp. 1–8.

[2] K. Nunna and S. Doolla, "Multiagent-based distributed-energy-resource management for intelligent microgrids," *IEEE Trans. Ind. Electron.*, vol. 60, no. 4, pp. 1678–1687, Apr. 2013.

[3] U. FERC, "Wholesale competition in regions with organized electric markets," 2008. [Online]. Available: http://www.ferc.gov/whats-new/comm-meet/2008/101608/E-1.pdf

[4] A. Timbus, M. Larsson, and C. Yuen, "Active management of distributed energy resources using standardized communications and modern information technologies," *IEEE Trans. Ind. Electron.*, vol. 56, no. 10, pp. 4029–4037, Oct. 2009.

[5] J. C. Vasquez, J. M. Guerrero, J. Miret, M. Castilla, and L. G. De Vicuna, "Hierarchical control of intelligent microgrids," *IEEE Ind. Electron. Mag.*, vol. 4, no. 4, pp. 23–29, Dec. 2010.

[6] S. Chakraborty, M. D. Weiss, and M. G. Simes, "Distributed intelligent energy management system for a single-phase high-frequency AC microgrid," *IEEE Trans. Ind. Electron.*, vol. 54, no. 1, pp. 97–109, Feb. 2007.

[7] K. Nunna and S. Doolla, "Intelligent demand side management in smart-microgrids," in *Proc. IEEE Int. Workshop Intell. Energy Syst.*, Nov. 2013, pp. 125–130.

[8] J. Eyer and G. Corey, "Energy storage for the electricity grid: Benefits and market potential assessment guide," Sandia Nat. Lab., Albuquerque, NM, USA, Tech. Rep. SAND2010-0815, 2010, pp. 69–73.

[9] J. Iannucci and S. Schoenung, "Energy storage concepts for a restructured electric utility industry," Sandia Nat. Lab., Albuquerque, NM, USA, Tech. Rep. Tech. Rep. SAND2010-1550, 2000.

[10] H. Oh, "Optimal planning to include storage devices in power systems," *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1118–1128, Aug. 2011.

[11] M. Parvania, M. F.-Firuzabad, and M. Shahidehpour, "ISO's optimal strategies for scheduling the hourly demand response in day-ahead markets," *IEEE Trans. Power Syst.*, vol. 29, no. 6, pp. 2636–2645, Nov. 2014.

[12] K. Moslehi and A. B. R. Kumar, "Autonomous resilient grids in an IoT landscape vision for a nested transactive grid," *IEEE Trans. Power Syst.*, vol. 34, no. 5, pp. 4089–4096, Sep. 2019.

[13] X. Lee *et al.*, "Virtual storage-based DSM with error-driven prediction modulation for microgrids," *IEEE Access*, vol. 7, pp. 71109–71118, 2019.

[14] K. Nunna and D. Srinivasan, "Multiagent-based transactive energy framework for distribution systems with smart microgrids," *IEEE Trans. Ind. Inform.*, vol. 13, no. 5, pp. 2241–2250, Oct. 2017.

[15] T. Morstyn, A. Teytelboym, and M. D. McCulloch, "Designing decentralized markets for distribution system flexibility," *IEEE Trans. Power Syst.*, vol. 34, no. 3, pp. 2128–2139, May 2019.

[16] M. Davison, J. Cranney, T. Summers, and C. D. Townsend, "Decentralised energy market for implementation into the intergrid concept—Part I: Isolated system," in *Proc. 7th Int. Conf. Renew. Energy Res. Appl.*, Oct. 2018, pp. 80–87.

[17] Z. Li, S. Bahramirad, A. Paaso, M. Yan, and M. Shahidehpour, "Blockchain for decentralized transactive energy management system in networked microgrids," *Electr. J.*, vol. 32, no. 4, pp. 58–72, 2019.

[18] S. A. Janko and N. G. Johnson, "Scalable multi-agent microgrid negotiations for a transactive energy market," *Appl. Energy*, vol. 229, pp. 715–727, 2018.

[19] Z. Suli, M. Zhongjing, and L. Xiangdong, "Optimal microgrid economic operations under progressive second price auction mechanisms," in *Proc. 32nd Chin. Control Conf.*, Jul. 2013, pp. 8891–8896.

[20] M. A. Ortega-Vazquez, "Optimal scheduling of electric vehicle charging and vehicle-to-grid services at household level including battery degradation and price uncertainty," *IET Gener., Transmiss. Distrib.*, vol. 8, no. 6, pp. 1007–1016, Jun. 2014.

[21] Y. L. M. Guo and J. Malec, "A new Q-learning algorithm based on the metropolis criterion," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 34, no. 5, pp. 2140–2143, Oct. 2004.

[22] J. Bialek, "Tracing the flow of electricity," *Proc. Inst. Elect. Eng.—Gener., Transmiss. Distrib.*, vol. 143, no. 4, pp. 313–320, Jul. 1996.

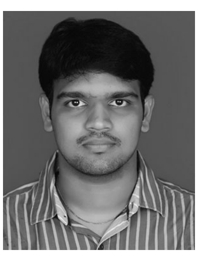
[23] M. Vukasovic and S. Skuletic, "Implementation of different methods for PTDF matrix calculation in flow-based coordinated auction," in *Proc. Int. Conf. Power Eng., Energy Elect. Drives*, 2007, pp. 791–795.

[24] Y. Du *et al.*, "A cooperative game approach for coordinating multi-microgrid operation within distribution systems," *Appl. Energy*, vol. 222, pp. 383–395, 2018.

[25] Energy Matters, "Australian solar feed-in tariffs," 2019. [Online]. Available: https://www.energymatters.com.au/rebates-incentives/feedintariff/
[26] Y. He, B. Venkatesh, and L. Guan, "Optimal scheduling for charging and discharging of EVs," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1095–1105, Sep. 2012.

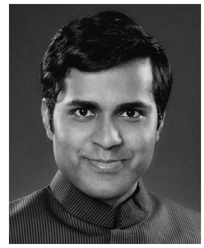
**H. S. V. S. Kumar Nunna** (Member, IEEE) received the M.Tech. degree in industrial power and automation from the National Institute of Technology Calicut, Kozhikode, India, in 2010, and the Ph.D. degree in power systems from the Indian Institute of Technology Bombay, Mumbai, India, in 2014.

From January 2015 to June 2017, he was a Postdoctoral Fellow with the Center for Green Energy Management and Smart Grids, National University of Singapore, Singapore. Since September 2017, he has been an Assistant Professor with the Department of Electrical and Computer Engineering, School of Engineering and Digital Sciences, Nazarbayev University, Nur-Sultan, Kazakhstan. His current research interests include transactive energy systems, smart microgrids, and energy blockchain.



**Anudeep Sesetti** received the bachelor's degree in electrical and electronics engineering from Andhra University, Visakhapatnam, India, in 2010, the M.Tech. degree in energy science and engineering from the Indian Institute of Technology Bombay, Mumbai, India, in 2015.

Since May 2019, he has been a Senior Analytics Engineer with the Digital Business Unit, Enphase Energy, Bangalore, India, where he has been focusing on developing analytics and solutions for Homeowners worldwide, who installed Enphase Solar System. Before joining Enphase, he was with Robert Bosch, Bangalore, and worked on industrial energy/process optimization from July 2015 to April 2019. His current research interests include energy analytics to solar and industrial process, transactive energy systems, and smart microgrids.



**Akshay Kumar Rathore** (Senior Member, IEEE) received the M.Tech. degree in electrical machines and drives from the Indian Institute of Technology, Banaras Hindu University, Varanasi, India, in 2003, and the Ph.D. degree in power electronics from the University of Victoria, Victoria, BC, Canada, in 2008.

He had two subsequent Postdoctoral Research Appointments with the University of Wuppertal, Wuppertal, Germany, and the University of Illinois at Chicago, Chicago, IL, USA. From November 2010 to February 2016, he was an Assistant Professor with the Department of Electrical and Computer Engineering, National University of Singapore, Singapore. He is currently an Associate Professor with the Department of Electrical and Computer Engineering, Concordia University, Montreal, QC, Canada. He has authored or coauthored more than 200 research papers published in international journals and conferences, including 73 IEEE Transactions. His research is mainly focused on current-fed converters and multilevel inverters. He is leading the area of current-fed power electronics and contributed to analysis, design, and development of new classes of such converters.

**Suryanarayana Doolla** (Senior Member, IEEE) received the M.Tech. degree in energy systems and engineering from the Indian Institute of Technology Bombay, Mumbai, India, in 2002, and the Ph.D. degree in power systems from the Indian Institute of Technology Delhi, New Delhi, India, in 2007.

He is currently a Professor with the Department of Energy Science and Engineering, Indian Institute of Technology Bombay. His research interests include smart microgrids, communication protocol for power systems, grid integration of distributed energy resources, and demand-side management.