SEED: QoS-Aware Sustainable Energy Distribution in Smart Grid

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Abstract—In this paper, the problem of ensuring reliable energy distribution in smart grid is studied, while considering that each customer is connected with multiple micro-grids. In the traditional smart grid, each customer is connected with a single micro-grid. Additionally, in the existing literature, some researchers proposed energy distribution schemes considering the presence of multiple micro-grids. However, none of these existing schemes consider that the customers can consume energy from multiple micro-grids simultaneously, which can essentially enhance the quality of service (QoS) in energy distribution, as it aids in reducing the transmission loss and increasing the profit of the micro-grids, while the customers pay less. To address the aforementioned problem, we design a sustainable energy distribution scheme, named SEED, to decide the distributed energy request vector, while ensuring high QoS in terms of energy availability and the price charged by the micro-grids in smart grid. We use an evolutionary game to ensure that the energy load is optimally distributed among the micro-grids and each micro-grid gets an equal opportunity to earn a profit. Through simulation, we observe that using SEED, renewable energy consumption per customer improves by 14.05 percent while reducing the cost by 29.87 percent. In other words, SEED ensures a sustainable environment by reducing the CO_2 emission by 14.05 percent, while reducing non-renewable energy consumption from the main grid. Additionally, the profit of each micro-grid increases by 58.32 percent.

Index Terms—Distributed renewable energy request, micro-grid, smart grid, sustainable energy distribution, quality of service, evolutionary game

1 Introduction

Smart grid [1] is an emerging energy distribution architecture, which aims to modernize the conventional energy distribution by combining with overlaying communication networks to acquire high reliability. It is conceptualized as a cyber-physical system which is a composite of different models such as generation, transmission, distribution, and usage, for ensuring efficiency and robustness of the electric network. Unlike traditional distribution networks, where the energy is generated from non-renewable resources and distributed centrally using the main grid, smart grid envisions the distributed energy generation using renewable energy resources to *reduce the carbon footprint*. Moreover, smart grid enables the customers to interact with the energy distributor in real-time and to pay accordingly. In smart grid, a set of renewable energy generation units, termed as micro-grids, are expected to serve a small geographical area having negligible CO_2 emission. The customers request energy to the micro-grids using demand-side energy distribution based on the real-time communication infrastructure.

To reduce the carbon footprint, the micro-grids use typically renewable energy resources — geothermal heat, wind power, solar energy, and biomass energy for generating energy. Hence, the amount of generated energy for the micro-grids varies over time. Additionally, the load on the micro-grids varies due to the energy consumption behavior of the customers. Hence, if the customers request a higher amount of energy than the energy generated by the micro-grids, they have to wait for a notable duration of time to get served. Otherwise, they pay higher to get services in the requested time-slot. To address this issue in the traditional smart grid, the micro-grids, having energy deficiency, request other micro-grids to supply the required energy. As a result, some units of energy are lost through the energy transmission process. On the other hand, in the existing literature, the researchers considered that the availability of multiple micro-grids for each customer will be economical [2]. Consequently, the quality of service (QoS) of energy distribution increases, thereby the customers get their required energy without paying high and waiting for a long duration. On the other hand, the micro-grids ensure a profit by providing the generated energy to the customers, while deciding an optimum price [3]. In the existing literature, the researchers considered that the customers decide an optimal micro-grid to serve the energy requirement. However, we can further enhance the QoS of the energy distribution by considering that the customers can consume energy from a subset of micro-grids as per their requirement, which situation is not been considered in the existing literature. This necessitates the design of a sustainable energy

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management scheme for smart grid in the presence of multiple micro-grids.

In this work, we use evolutionary game to propose SEED, a scheme for sustainable energy requests distribution in smart grid, to ensure high QoS. We measure QoS in terms of consumed energy and price charged by the micro-grids. We argue that the aforementioned problem can be mapped to the *bin packing problem* [4], which is an NP-hard problem. Therefore, to obtain a stable solution in polynomial time, we use evolutionary game theory in SEED. The proposed scheme, SEED, guarantees high utilization of the generated energy, thereby ensuring an increase in the profit of the micro-grids. In SEED, each micro-grid aims to maximize its profit while ensuring proper utilization of the generated energy. On the other hand, the objective of each customer is to reach the evolutionary equilibrium state using SEED. We consider that the meter data management system (MDMS) acts as a centralized coordinator. With the help of MDMS, each customer generates an individual distributed energy request vector, i.e., a set of the fractional amount of required energy to the micro-grids unlike the traditional smart grid, where each customer consumes from a single micro-grids. On the other hand, while deciding the price per unit of energy, each micro-grid considers the aggregated energy requested by the customers. Thus, SEED ensures the reduction in the transmission loss and the increase in the profit of the micro-grids, however, the customers are charged less for consuming the required amount of energy. In summary, the specific *contributions* of this work are as follows:

1) We present a *sustainable energy distribution* scheme, named SEED, for managing the real-time energy consumption of the customers in the presence of multiple micro-grids.
2) The customers use an evolutionary game to decide their optimal renewable energy consumption strategies for satisfying their requirements while reducing carbon footprints. On the other hand, each micro-grid decides an optimal price to be charged, thereby ensuring a high profit.
3) In SEED, we present two algorithms to decide the optimal strategies for the customers and micro-grids, respectively.
4) We present extensive simulation results to evaluate the performance of SEED in comparison with the existing schemes for smart grid in the literature.

2 Related Works

In the past few years, many research works on smart grid emanated, viz., [5], [6], [7], [8], [9], [10], [11]. The existing literature are divided into two categories — (a) energy distribution schemes, and (b) pricing models in smart grid.

Some of the energy distribution schemes proposed in the existing literature are discussed here. Such and Hill [5] proposed a distributed system to control wind generation in the context of smart grid. Molderink *et al.* [12] and Erol-Kantarci and Mouftah [13] proposed different energy management schemes using energy consumption timing patterns such as on-peak and off-peak hours. The authors considered that the customers wait for being served while paying less. Otherwise, they pay high to get service instantaneously. Farzan *et al.* [8] proposed a forecasting-based energy management model while considering two aspects such as short- and long-term load calculations. In another work, Maffei *et al.* [14] proposed a scheme to handle uncertainties by forecasting the amount of energy to be supplied and demanded. Bahrami *et al.* [15] proposed a potential game-based decentralized energy distribution scheme while consider the dynamic pricing. Pal *et al.* [16] proposed an online algorithm for clustering the customers based on their consumption profile and estimate future energy demand. Samadi *at al.* [10] and Mediwaththe *et al.* [11] designed energy management schemes in the presence of prosumers, where the customers having excess energy supplies energy to the micro-grids. Shabshab *et al.* [17] proposed a scheme to reduce the peak load and maintain a near-constant demand in military microgrids. On the other hand, Mondal *et al.* [2] studied an energy management scheme while considering that the customers are equipped with storage devices. In another work, Marashi *et al.* [18] proposed a scheme for quantitative analysis of reliability in smart grid and studied a mitigation scheme to ensure uninterrupted services.

On the other hand, Bakker *et al.* [19] formulated a dynamic pricing-based energy management scheme using the congestion game. In another work, Misra *et al.* [6] designed a pricing scheme for PHEVs while considering the geographical distribution, i.e., local and roaming. Correa-Florez *et al.* [20] proposed a scheme to reduce the energy distribution cost while considering that the energy requirement information for shift-able and fixed appliances is known *a priori*. Kamyab *et al.* [9] proposed a pricing-based energy management scheme in the presence of non-cooperative service providers and customers. In another work, Moradipari *et al.* [21] proposed a scheme for optimal pricing-based energy distribution for PHEVs. The authors also presented a routing scheme for ensuring efficient energy distribution in smart grid.

In the existing literature, there exist few works, viz. [22], [23], [24], [25], on optimized load-distribution for different distributed architecture. Monnier *et al.* [22] proposed a genetic algorithm based task scheduling scheme for handling multiple independent periodic macro tasks. Friedrich *et al.* [26] studied the evolutionary algorithm and genetic algorithm for smoothing the noisy-data without using any noise handling strategy. This approach can be used for distributing the workload while having noisy information about the data-offloading. In another work, Pankratz [23] studied the dynamic pick-up and delivery problem, distributively, using a genetic algorithm. Similarly, Jin *et al.* [25] proposed a scheduling scheme for task mapping using a genetic algorithm.

Synthesis. In the existing schemes proposed for smart grid, the researchers focused on pricing models along with energy distribution to ensure utilization of generated renewable energy. In these works, the researchers focused on minimizing the charged price per unit of renewable energy and earned revenue by the micro-grids. However, these schemes assume that the customers consume energy

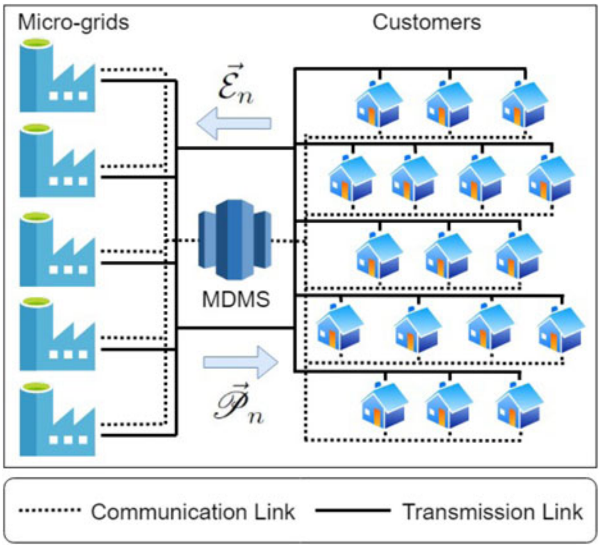

Fig. 1. System model for SEED.

from a single micro-grid, thereby they decide the amount of renewable energy to be consumed in each time slot. None of these works consider the presence of multiple micro-grids, where each customer can consume energy from multiple micro-grids, simultaneously, as per his/her requirement. On the other hand, in the existing literature, the researchers also proposed schemes based on a genetic algorithm to ensure optimized load-distribution for service offload in a different distributed architecture. However, none of the schemes can be used for energy distribution in smart grid in the presence of multiple micro-grids. Hence, there is a need to design a scheme for addressing the problem of ensuring reliable energy distribution in smart grid while considering that each customer is connected with multiple micro-grids.

3 System Model

We consider an sustainable energy management system having several micro-grids and multiple customers, and the micro-grids form a *coalition* [7], as shown in Fig. 1. Within a coalition, each customer $n \in \mathcal{N}$, where $\mathcal{N}$ is the set of customers, requests a subset of micro-grids $\Omega_n \subseteq \mathcal{M}$, where $\mathcal{M}$ is the set of available micro-grids. Based on the interaction with Ω_n micro-grids and the *price vector* $\vec{\mathscr{P}}_n$, defined in Definition 2, customer n decides the *distributed renewable energy request vector* $\vec{\mathcal{E}}_n$, defined in Definition 1. We present a list of the symbols used in the paper in Table 1 We consider that customer n has X_n amount of energy requirement, and requests $e_n^{(m)}$ amount of energy to each micro-grid m. Therefore, we have:

$$X_n = \sum_{m \in \Omega_n} e_n^{(m)}. \tag{1}$$

Definition 1. *The distributed renewable energy request vector $\vec{\mathcal{E}}_n$ is the collection of $|\Omega_n|$ number of energy request components. Hence, it is represented as $\vec{\mathcal{E}}_n = \{e_n^{(m)} | m \in \Omega_n\}$.*

Definition 2. *The price vector $\vec{\mathscr{P}}_n$ is represented as $\vec{\mathscr{P}}_n = \{p^{(m)} | m \in \Omega_n\}$, where $p^{(m)}$ denotes the price per unit renewable energy decided by micro-grid m.*

TABLE 1
List of Symbols

Symbol	Description
$\mathcal{N}$	Set of customers
$\mathcal{M}$	Set of available micro-grids
$\vec{\mathcal{E}}_n$	Distributed renewable energy request vector for customer n
$\vec{\mathscr{P}}_n$	Price vector for customer n
$\vartheta_n(\cdot)$	Utility function of customer n
$\mathbb{P}^{(m)}$	Pricing function of the micro-grid m
$e^{(m)}$	Amount of energy requested to micro-grid m
$e_n^{(m)}$	Amount of energy requested to micro-grid m by customer n
X_n	Amount of energy required by customer n
Ω_n	Subset of micro-grids connected to customer n
$\mathcal{N}^{(m)}$	Set of customers requests energy to micro-grid m
$\mathcal{G}^{(m)}$	Amount of energy generated by micro-grid m
$p^{(m)}$	Price per unit amount of energy by micro-grid m
$\epsilon^{(m)}$	Marginal profit coefficient for micro-grid m
$\eta_n^{(m)}$	Proportion of required energy requested to the micro-grid $m \in \Omega_n$
$\eta^{(m)}(t)$	Population share of micro-grid m
$\dot{\eta}^{(m)}(t)$	Replicator dynamics of each micro-grid m
$\boldsymbol{\eta}$	Population state of the micro-grids

Therefore, the profit function of the micro-grid m, $\mathcal{P}r^{(m)}$, is defined as follows:

$$\mathcal{P}r^{(m)} = p^{(m)} \sum_{n \in \mathcal{N}^{(m)}} e_n^{(m)} - c^{(m)} \mathcal{G}^{(m)}, \tag{2}$$

where $\mathcal{N}^{(m)}$ defines the set of customers requested renewable energy to micro-grid m; and $\mathcal{G}^{(m)}$ and $c^{(m)}$ denote the amount of generated renewable energy and the generation cost incurred per unit energy by micro-grid m, respectively. Hence, the total renewable energy requested $e^{(m)}$ to micro-grid m is defined as follows:

$$e^{(m)} = \sum_{n \in \mathcal{N}^{(m)}} e_n^{(m)}. \tag{3}$$

Since, the renewable energy generated $\mathcal{G}^{(m)}$ by each micro-grid m is fixed, the energy requested $e^{(m)}$ by the customers must satisfy the following constraint:

$$\mathcal{G}^{(m)} \geq e^{(m)}. \tag{4}$$

In case of $\sum_{m \in \mathcal{M}} \mathcal{G}^{(m)} < \sum_{m \in \mathcal{M}} e^{(m)}$, the micro-grids request the main grid to serve the deficit amount of energy. Based on $e^{(m)}$, each micro-grid m calculates $p^{(m)}$ using a dynamic pricing coefficient, as defined below:

$$p^{(m)} = \begin{cases} K, & \text{if } e^{(m)} \leq \mathcal{G}^{(m)} \\ \lim_{\theta \to \infty} \theta, & \text{otherwise,} \end{cases} \tag{5}$$

$$K = \begin{cases} c^{(m)} + \epsilon^{(m)}, & \text{if } p^{(m)} < [c^{(m)} + \epsilon^{(m)}] \\ K', & \text{otherwise,} \end{cases} \tag{6}$$

where $\epsilon^{(m)}$ denotes the *marginal profit coefficient* for micro-grid m, defined in Definition 3; $K' = A^{(m)} + B^{(m)} e^{(m)} + C^{(m)} [e^{(m)}]^2$ [27]; $A^{(m)}$, $B^{(m)}$, and $C^{(m)}$ are constants. Based on the optimum price vector $\vec{\mathscr{P}}_n^*$, each customer n tries to reduce his/her energy consumption cost by deciding energy consumption strategy — the optimum renewable energy request vector $\vec{\mathcal{E}}_n^*$, where $\vec{\mathscr{P}}_n^* = \{p^{(m)*}|m \in \Omega_n\}$, and $\vec{\mathcal{E}}_n^* = \{e_n^{(m)*}|m \in \Omega_n\}$. Here, $p^{(m)*}$ and $e_n^{(m)*}$ denote the optimal price per unit renewable energy decided by micro-grid m and the optimal amount of renewable energy requested to micro-grid m by customer n, respectively.

Definition 3. *The marginal profit coefficient $\epsilon^{(m)}$ for micro-grid m is evaluated as the revenue earned by supplying unit amount of renewable energy generated. Therefore, we have:*

$$\epsilon^{(m)} = \left[\frac{\partial p^{(m)}}{\partial e^{(m)}} - \frac{\partial c^{(m)}}{\partial e^{(m)}}\right]\Bigg|_{\partial e^{(m)}=1}. \tag{7}$$

For each micro-grid m, we assume that price $p^{(m)}$ is higher than cost $c^{(m)}$, therefore $\epsilon^{(m)} > 0$.

Therefore, the energy demanded $e_n^{(m)}$ by customer n needs to satisfy the constraints given in Equations (1) and (4). On the other hand, the price $p^{(m)}$ is also dependent on $e^{(m)}$, as depicted in Equations (5) and (6).

4 SEED: The Proposed Sustainable Energy Distribution Scheme

In this work, we model the energy trading between the customers and the micro-grids using *evolutionary game theory*, based on the work of Shivshankar and Jamalipour [28]. We argue that the evolutionary game is the most suitable mathematical tool to model the aforementioned scenario, as described below.

4.1 Justification for Use of Evolutionary Game

In SEED, the customers aim to minimize the cost of energy consumption by distributing the energy load among the micro-grids. The MDMS acts as the centralized coordinator among the micro-grids, thereby ensuring the optimal load balancing among the micro-grids. We argue that the sustainable energy distribution problem addressed in SEED can be mapped to the *bin packing problem* [4], which is an NP-hard problem. The justification of the claim is discussed below for better understanding.

Justification for Considering SEED as an NP-Hard Problem

As we know that the traditional bin packing problem deals with packing different volumes of objects into a finite set of bins having finite volumes. The objective of the aforementioned problem is to minimize the number of bins. Similarly, in SEED, each customer in smart grid with the help of AMI, MDMS, and SCADA, decides the finite volume of energy to be requested to multiple micro-grids, each having a finite amount of generated energy. Therefore, we claim that the sub-problem is SEED resembles the traditional bin packing problem, which is an NP-hard problem. Additionally, in SEED, the energy generated by the micro-grids is distributed among the customers, where each micro-grid does not have the common knowledge of the amount of energy generated by the other micro-grids. Therefore, we argue that SEED is an NP-hard problem.

Therefore, using combinatorial optimization approaches, the aforementioned problem cannot be solved in polynomial time. Moreover, evolutionary game theory ensures a stable solution, unlike other game-theoretic approaches where multiple Nash equilibrium solutions are feasible. Using the Lyapunov function [29], we can observe that the SEED achieves a stable solution. On the other hand, in the existing literature [22], [23], [24], [25], the researchers proposed to use the genetic algorithm for service offload in distributed architectures. However, in the context of smart grid, we cannot use the genetic algorithm in energy distribution in the presence of multiple micro-grids due to the following reasons:

1) The amount of energy to be consumed from the micro-grids by each customer is a continuous function. Hence, the evolutionary game is most suitable for this problem. However, for discrete function optimization, we may use the genetic algorithm.
2) With the increase in population, the complexity of genetic algorithms increases significantly, which is not the case for the evolutionary game.
3) Genetic algorithm ensures a local optimum solution, as the final solution depends on the chosen initial vector. However, the evolutionary game ensures a globally optimal solution irrespective of the initial population distribution, i.e., population share.

Moreover, in smart grid, each micro-grid has its MDMS and SCADA system, hence, in the presence of multiple micro-grids, each micro-grid does not have common knowledge about the other micro-grids. Therefore, we cannot use convex optimization with relaxed constraints to solve this problem in smart grid having multiple micro-grids. On the other hand, the evolutionary game-theoretic approach considers the population of the players and generates all the possible combinations of strategies. In this work, SEED enables the following properties of the evolutionary game.

1) Considering that the micro-grids are rational, we cannot guarantee the existence of a stable and single Nash equilibrium in distributive energy request. However, SEED enables the presence of stable equilibrium by using the evolutionary game. We argue that the equilibrium achieved in SEED is stable, as the players, i.e., the energy requested by the customers, cannot achieve a high payoff by deviating.
2) In SEED, the dynamics of selected strategies are captured using evolutionary game theory. Here, each customer observes others and chooses the appropriate strategy based on the knowledge gained by observation. Eventually, the customers adopt the strategies to reach the evolutionary equilibrium solution.

We argue that the interaction among the customers and the micro-grids in the context of SEED can be modeled efficiently using the evolutionary game.

4.2 Game Formulation

We consider that each customer n acts as a player decides the distributed renewable energy request vector $\vec{\mathcal{E}}_n$ and ensures an optimal energy consumption cost. In SEED, the amount of required energy defines the population. In particular, given the renewable energy generation capacity of each micro-grid m, the customers compete among themselves to consume energy. Hence, each customer n evolves by changing the component values of the energy request vector to ensure optimal utilization of generated renewable energy. The evolutionary equilibrium, i.e., an optimal solution, in SEED substantiates that each customer receives an equivalent payoff. The components of the SEED scheme are described below:

(i) Each customer n decides the distributed renewable energy request vector $\vec{\mathcal{E}}_n$ based on the total demanded energy X_n and the known price vector $\vec{\mathscr{P}}_n$ determined by the micro-grids Ω_n.

(ii) The utility function $\boldsymbol{\vartheta}_n(\cdot)$ of customer n, that captures the benefit of $\vec{\mathcal{E}}_n$, needs to be maximized.

(iii) The pricing function $\mathbb{P}^{(m)}$ of the micro-grid m is defined as a linear function. Mathematically,

$$\mathbb{P}^{(m)}(e^{(m)}) = p^{(m)} e^{(m)}. \tag{8}$$

(iv) In SEED, the population is defined as the set of distributed renewable energy requests in a coalition. We assume that each customer n has a finite energy demand of X_n. In other words, the population corresponds to each customer $n \in \mathcal{N}$ is finite.

(v) The payoff $\boldsymbol{\vartheta}_n$ of each customer n is determined by his/her net utility.

4.2.1 Utility function for the Customers

For each customer n, the utility function $\boldsymbol{\vartheta}_n$ represents the level of satisfaction by consuming the total amount of required energy X_n. We consider $\boldsymbol{\vartheta}_n$ to be a concave function. $\boldsymbol{\vartheta}_n$ is defined as follows:

$$\boldsymbol{\vartheta}_n = \sum_{m \in \Omega_n} \vartheta_n^{(m)}, \tag{9}$$

where $\vartheta_n^{(m)}$ is the partial level of satisfaction of each customer n connected with micro-grid m. The net payoff of each customer n choosing micro-grid m is defined as follows:

$$\vartheta_n^{(m)} = \mathcal{U}(e_n^{(m)}, \mathcal{N}^{(m)}) - \mathbb{P}^{(m)}(e_n^{(m)}). \tag{10}$$

We assume that $\mathcal{U}(e_n^{(m)}, \mathcal{N}^{(m)})$ is a strictly increasing concave non-negative function, as each customer n tries to consume higher units of renewable energy from each micro-grid m to fulfill his/her energy requirements. $\mathbb{P}^{(m)}$ is the pricing function, as mentioned in Equation (8). Therefore, we can rewrite Equation (9) to calculate the net utility as follows:

$$\boldsymbol{\vartheta}_n = \sum_{m \in \Omega_n} [\mathcal{U}(e_n^{(m)}, \mathcal{N}^{(m)}) - \mathbb{P}^{(m)}(e_n^{(m)})] \tag{11}$$

$$\vartheta_n^{(m)} = e_n^{(m)} p(m) \frac{\mathcal{G}^{(m)}}{\sum_{m \in \Omega_n} e_n^{(m)}} - p^{(m)} e_n^{(m)}. \tag{12}$$

We consider that $\eta_n^{(m)}$ is the proportion of required energy requested to the micro-grid $m \in \Omega_n$. Therefore,

$$e_n^{(m)} = X_n \eta_n^{(m)}. \tag{13}$$

Hence, we rewrite the net utility function, defined in Equation (12), as follows:

$$\boldsymbol{\vartheta}_n = \sum_{m \in \Omega_n} [e_n^{(m)} p(m) \frac{\mathcal{G}^{(m)}}{\sum_m X_n \eta_n^{(m)}} - p^{(m)} X_n \eta_n^{(m)}]. \tag{14}$$

Replicator Dynamics and Evolutionary Equilibrium

In the evolutionary game, a player, which can replicate him/her/it-self through evolution such as mutation and selection, is called a *replicator*. In the evolutionary game, the change in the decision of a replicator is termed as *replicator dynamics*. In Definition 4, we define the replicator dynamics in the context of the proposed scheme, SEED.

Definition 4. *In SEED, replicator dynamics is a set of first-order ordinary differential equations to model the reproduction of the strategies, i.e., the change in the amount of renewable energy requested to the micro-grids. Additionally, it controls the speed of convergence of choosing strategies to achieve the evolutionary equilibrium.*

In evolutionary game, replicator dynamics provides information about the strategies chosen by the players individually. In SEED, we consider that each player chooses a mixed strategy from a set of finite strategies, individually. The players form the population choosing strategy m, $\eta^{(m)}(t)$, termed as *population share*, which is defined as follows:

$$\eta^{(m)}(t) = \frac{e^{(m)}(t)}{\sum_{n \in \mathcal{N}} X_n} \tag{15}$$

Therefore, the change in population share, i.e., the replicator dynamics, $\dot{\eta}^{(m)}(t)$ of each micro-grid m is defined as follows:

$$\dot{\eta}^{(m)}(t) = \eta^{(m)}(t)(\boldsymbol{\vartheta}^{(m)}(t) - \bar{\boldsymbol{\vartheta}}(t)), \tag{16}$$

where $\boldsymbol{\vartheta}^{(m)}(t) = \sum_{n \in \mathcal{N}^{(m)}} \vartheta_n^{(m)}(t)$, $\bar{\boldsymbol{\vartheta}}(t)$ is the average payoff of the entire population calculated by the MDMS; and the population state is defined by $\boldsymbol{\eta} = [\eta^{(1)}, \ldots, \eta^{(m)}, \ldots, \eta^{(|\mathcal{M}|)}]$. In SEED, the equilibrium state can be defined as a set of stable points derived using the replicator dynamics.

Revenue Function of the Micro-Grids

Revenue function $\boldsymbol{\psi}_m$ defines the profit earned by distributing requested renewable energy $e^{(m)}$ to the customers. We define the revenue function as follows:

$$\boldsymbol{\psi}_m = \mathbb{P}^{(m)} e^{(m)}, \quad \forall m \in \mathcal{M}. \tag{17}$$

Based on Equations (5) and (6), each micro-grid m decides an optimal price coefficient $p^{(m)}$. While deciding the

$$e_n^{(m)} = \frac{-[A^{(m)} + (B^{(m)} + 2C^{(m)}) e_{-\boldsymbol{n}}^{(m)}] \pm \sqrt{[A^{(m)} + (B^{(m)} + 2C^{(m)}) e_{-\boldsymbol{n}}^{(m)}]^2 - 4(B^{(m)} + C^{(m)})(e_{-\boldsymbol{n}}^{(m)} - \gamma)}}{2(B^{(m)} + C^{(m)})}. \tag{20}$$

price per unit of renewable energy, each micro-grid takes into consideration that a high value of $p^{(m)}$ discourages customers to consume energy. On the other hand, the low value of $p^{(m)}$ reduces the revenue earned.

4.3 Evolutionary Equilibrium of SEED Scheme

In SEED, we consider that each customer is connected with multiple micro-grids in the coalition. Each customer adopts the strategy with a higher payoff, i.e., evolves, depending on the fact that the proposed scheme is repetitive. In SEED, based on Equation (16), the speed of adaptation of strategies is controlled by each customer n by varying the *gain of the replicator dynamics* α_n, defined in Definition 5.

Definition 5. *The gain of the replicator dynamics α_n is a constant, and controls the speed of observation and adaptation of the strategies. α_n is calculated as follows:*

$$\alpha_n = \frac{\dot{\eta}^{(m)}(\cdot)}{\eta_n^{(m)}(\cdot)(\boldsymbol{\vartheta}_n^{(m)}(\cdot) - \bar{\boldsymbol{\vartheta}}_n(\cdot))}, \tag{18}$$

where $\eta_n^{(m)} = \frac{e_n^{(m)}}{X_n}$ and $\bar{\boldsymbol{\vartheta}}_n(\cdot)$ is the average payoff customer n by consuming X_n units of renewable energy from Ω_n micro-grids. Mathematically,

$$\bar{\boldsymbol{\vartheta}}_n(\cdot) = \sum_{m\in\Omega_n} \eta_n^{(m)} \boldsymbol{\vartheta}_n^{(m)}. \tag{19}$$

Thus, each customer n evolves, i.e., changes its strategy, depending on the replicator dynamics shown in Equation (18).

In SEED, the evolutionary equilibrium is a solution for deciding the distributed renewable energy request vector for the customers within a coalition. In this section, we try to evaluate the *evolutionary stability* of SEED, as mentioned in Theorem 1. The evolutionary equilibrium in SEED signifies that any customer or micro-grid cannot obtain higher profit by deviating from the equilibrium condition [30].

Theorem 1. *Given that $\mathcal{G}^{(m)}$ is same for each micro-grid m, $e_n^{(m)}$ is expressed as in Equation (20), where $e_{-\boldsymbol{n}}^{(m)} = \sum_{i\neq n}^{i\in\mathcal{N}^{(m)}} e_i^{(m)}$, and γ is a constant and expressed as follows:*

$$\gamma = \frac{\sum_{m\in\Omega_n} e_n^{(m)} p^{(m)}}{|\Omega_n|}. \tag{21}$$

Proof. The replicator dynamics or each customer n is defined in Equation (18)[1]. Hence, at evolutionary equilibrium of SEED, the change in replicator dynamics is zero, i.e., $\eta_n^{(m)}(t) = 0$, where $\eta_n^{(m)}(t) > 0$. Therefore, we get:

$$\eta_n^{(m)}(t)(\vartheta_n^{(m)}(t) - \frac{\sum_{\tilde{m}\in\Omega_n} \vartheta_n^{(\tilde{m})}}{|\Omega_n|}) = 0. \tag{22}$$

Satisfying constraint $\eta_n^{(m)}(t) > 0$, from Equation (22), we get:

$$\vartheta_n^{(m)} = \frac{\sum_{\tilde{m}\neq m, \tilde{m}\in\Omega_n} \vartheta_n^{(\tilde{m})}}{1 - |\Omega_n|}. \tag{23}$$

Therefore, we evaluate:

$$e_n^{(m)} p^{(m)} \left(\frac{\mathcal{G}^{(m)}}{X_n} - 1\right) = e_n^{(\tilde{m})} p^{(\tilde{m})} \left(\frac{\mathcal{G}^{(\tilde{m})}}{X_n} - 1\right). \tag{24}$$

where $m \neq \tilde{m}$, $\{m, \tilde{m}\} \in \Omega_n$, and X_n is evaluated using Equation (1). If $\mathcal{G}^{(m)}$ is same for each micro-grid m, we argue that γ is constant using Equation (21). Therefore, we get $e_n^{(m)} = \frac{\gamma}{p^{(m)}}$. Therefore, from Equations (5) and (6), we get:

$$e_n^{(m)} = \begin{cases} \frac{\gamma}{c^{(m)} + \epsilon^{(m)}}, & \text{if } p^{(m)} < [c^{(m)} + \epsilon^{(m)}] \\ \frac{\gamma}{A^{(m)} + B^{(m)} \sum_{n\in\mathcal{N}^{(m)}} e_n^{(m)} + C^{(m)} [\sum_{n\in\mathcal{N}^{(m)}} e_n^{(m)}]^2}, & \text{otherwise.} \end{cases} \tag{25}$$

Hence, if $p^{(m)} \geq [c^{(m)} + \epsilon^{(m)}]$, we get:

$$\begin{aligned} & e_n^{(m)} [A^{(m)} + B^{(m)} \sum_{n\in\mathcal{N}^{(m)}} e_n^{(m)} + C^{(m)} \Big[\sum_{n\in\mathcal{N}^{(m)}} e_n^{(m)}]^2\Big] = \gamma \\ & \Rightarrow e_n^{(m)} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}, \end{aligned} \tag{26}$$

where $e_{-\boldsymbol{n}}^{(m)} = \sum_{\tilde{n}\neq n, \tilde{n}\in\mathcal{N}^{(m)}} e_n^{(m)}$; $a = (B^{(m)} + C^{(m)})$; $b = (A^{(m)} + B^{(m)} e_{-\boldsymbol{n}}^{(m)} + 2C^{(m)} e_{-\boldsymbol{n}}^{(m)})$; and $c = ([e_{-\boldsymbol{n}}^{(m)}]^2 - \gamma)$.

Therefore, using Equation (26), we prove that Equation (20) is true. □

Corollary 1. *Considering that each micro-grid m supplies the same unit of renewable energy to each customer n, $e_n^{(m)}$ is expressed as follows:*

$$e_n^{(m)} = \sqrt[3]{a + \sqrt{a^2 + b^3}} + \sqrt[3]{a - \sqrt{a^2 + b^3}} - c, \tag{27}$$

where $a = \frac{A^{(m)}}{3C^{(m)}[|\mathcal{N}^{(m)}|]^2} - \frac{[B^{(m)}]^2}{9C^{(m)}}$; $b = -\frac{[B^{(m)}]^3}{27[C^{(m)}|\mathcal{N}^{(m)}|]^3} + \frac{A^{(m)}B^{(m)}}{6[C^{(m)}]^2[|\mathcal{N}^{(m)}|]^3} - \frac{\gamma}{2C^{(m)}[|\mathcal{N}^{(m)}|]^2}$; *and* $c = \frac{B^{(m)}}{3C^{(m)}|\mathcal{N}^{(m)}|}$.

Proof. Based on the assumption considered in Corollary 1, we get:

$$\sum_{n\in\mathcal{N}^{(m)}} e_n^{(m)} = e_1^{(m)} + \cdots + e_{|\mathcal{N}^{(m)}|}^{(m)} = |\mathcal{N}^{(m)}| e_n^{(m)}. \tag{28}$$

Therefore, Equation (26) is rewritten as:

$$C^{(m)}[|\mathcal{N}^{(m)}|]^2 [e_n^{(m)}]^3 + B^{(m)} |\mathcal{N}^{(m)}| [e_n^{(m)}]^2 + e_n^{(m)} A^{(m)} - \gamma = 0. \tag{29}$$

We represent Equation (29) as follows:

$$[e_n^{(m)}]^3 + \alpha [e_n^{(m)}]^2 + \beta e_n^{(m)} + \rho = 0, \tag{30}$$

where $\alpha = (B^{(m)}|\mathcal{N}^{(m)}|)/(C^{(m)}[|\mathcal{N}^{(m)}|]^2)$, $\beta = A^{(m)}/(C^{(m)}[|\mathcal{N}^{(m)}|]^2)$, and $\rho = \gamma/(C^{(m)}[|\mathcal{N}^{(m)}|]^2)$. We denote $\omega = (e_n^{(m)} + \frac{\alpha}{3})$. Therefore, replacing $e_n^{(m)}$ with $(\omega - \frac{\alpha}{3})$, we get:

$$\begin{aligned} & \omega^3 + \left(\beta - \frac{\alpha^2}{3}\right)\omega + \left(\rho + \frac{2\alpha^3}{27} - \frac{\beta\alpha}{3}\right) = 0 \\ & \Rightarrow \omega^3 + \acute{a}\omega + \acute{b} = 0 \end{aligned} \tag{31}$$

where $\acute{a} = (\beta - \frac{\alpha^2}{3})$ and $\acute{b} = (\rho + \frac{2\alpha^3}{27} - \frac{\beta\alpha}{3})$.

By applying *Cardano's method* [31] on Equation (31), we get Equation (27). □

4.4 Proposed Algorithms

In order to reach the equilibrium in SEED, each customer needs to decide $\vec{\mathcal{E}}_n$ using Algorithm 1, while ensuring that the constraint in Equation (1) is satisfied. On the other hand, Algorithm 2 needs to be executed distributively by the MDMS with the help of information from the SCADA system associated with each micro-grid. Therefore, using Algorithm 2, each micro-grid decides $p^{(m)}$ based on the energy demanded by the customers as mentioned in Equations (5) and (6). In SEED, each customer executes *evolutionary game*-based energy consumption algorithm to obtain the evolutionary equilibrium point.

Algorithm 1. SEED Algorithm for each Customer n

INPUTS:
$\mathcal{M}$, $p^{(m)}$, $\mathcal{G}^{(m)}$, X_n, e_n^d, I_n
OUTPUT:
$\vec{\mathcal{E}}_n$ ▷ `Distributed renewable energy request vector`
PROCEDURE:
Decide $\vec{\mathcal{E}}_n$ while satisfying Equation (1);
do
 Calculate population share $\eta_n^{(m)}(\cdot)$ using Equation (13);
 Calculate $\vartheta_n^{(m)}(\cdot)$ using Equation (12);
 Calculate $\bar{\vartheta}_n(\cdot)$ using Equation (19);
 Calculate $\dot{\eta}_n^{(m)}(\cdot)$ using Equation (18);
while $(\dot{\eta}_n^{(m)}(\cdot) \neq 0)$;
Calculate $\vec{\mathcal{E}}_n$ based on modified $\eta_n^{(m)}(\cdot), \forall m \in \mathcal{M}$;
return $\vec{\mathcal{E}}_n$;

Algorithm 2. SEED Algorithm for each Micro-grid m

INPUTS:
$\mathcal{N}$, $c^{(m)}$, $\epsilon^{(m)}$, $\mathcal{G}^{(m)}$, $\{e_n^{(m)} | \forall n \in \mathcal{N}\}$
OUTPUT:
$p^{(m)}$ ▷ `Selling price cost coefficient`
PROCEDURE:
Calculating $e^{(m)}$ using Equation (3);
Calculating $p^{(m)}$ using Equations (5) and (6);
return $p^{(m)}$;

5 Performance Evaluation

5.1 Simulation Settings

To evaluate the performance of SEED, we randomly selected the positions of the micro-grids and customers in the MATLAB simulation platform. We considered that within a coalition [7], each customer requests energy from multiple micro-grids simultaneously. We initialized the values of the renewable energy consumption profile of the customers randomly, as mentioned in Table 2. Within a coalition, each micro-grid generates energy using renewable energy resources, thereby, the energy generation profile of the micro-grids is considered to be random. Therefore, each customer selects a set of micro-grids from available micro-grids, and requests each micro-grid partially, to maintain a balanced load over the micro-grids. Furthermore, by consuming renewable energy from the micro-grids, the customers ensure less carbon footprint unlike consuming non-renewable energy from the main grid. On the other hand, based on the energy requested by the customers, each micro-grid decides the price for each unit of renewable energy. Therefore, for simulation, we considered the input parameters mentioned in the Algorithms 1 and 2 and observed the change in the mentioned output parameters.

TABLE 2
Simulation Parameters

Parameter	Value
Simulation area	10 km × 10 km
Number of micro-grids	10
Number of customers	200–1000
Renewable energy generation cost	10 USD/MWh
Renewable energy request by each customer	20–90 MWh
Renewable energy produced by each micro-grid	200–500 MWh

5.2 Benchmarks

We compared the performance of SEED with three existing schemes – home energy management with storage (HoMeS) [2], Electric Vehicle Charging (EVC) [32], and price taking user (PTU) [33]. In HoMeS, Mondal *et al.* [2] considered that the users are equipped with storage devices. The authors studied the energy utilization profile of the customers using the multiple-leader-multiple-follower Stackelberg game. In EVC, Tushar *et al.* [32] used the Stackelberg game for energy trading among the PHEVs and smart grid. Each PHEV aims to optimize the amount of energy to be consumed for charging, and the smart grid tries to optimize the price per unit of energy. On the other hand, in PTU, Samadi *et al.* [33] proposed a scheme for maximizing the aggregated payoff of the customers with less energy generation cost. The authors tried to reduce power consumption while shifting loads to off-peak hours. However, they did not consider simultaneous energy requests to multiple micro-grids. Thus, using SEED, we can enhance the reliability of the energy management system over HoMeS, EVC, and PTU.

5.3 Performance Metrics

We evaluated the performance of SEED using the following metrics.

1) *Renewable Energy Consumed by Customers*. The average renewable energy consumed by each customer signifies the satisfaction factor of the customer. We define the average satisfaction factor as the ratio between the average consumed renewable energy by a customer and the average requested energy. Therefore, we infer that the higher energy consumption of the customers indicates that the micro-grids have less excess generated energy. On the other hand, the high average renewable energy consumption of the customers signifies less CO_2 emission, as we consider that after consuming from the micro-grids, the customers consume the remaining amount of energy from the main grid, which uses non-renewable resources for energy generation.

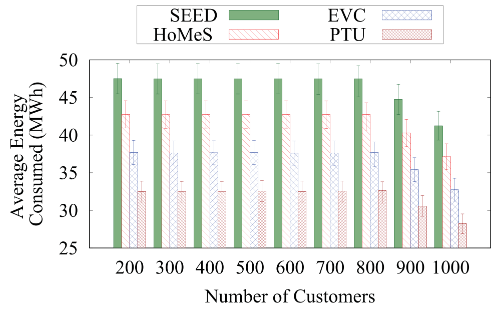

Fig. 2. Energy consumption.

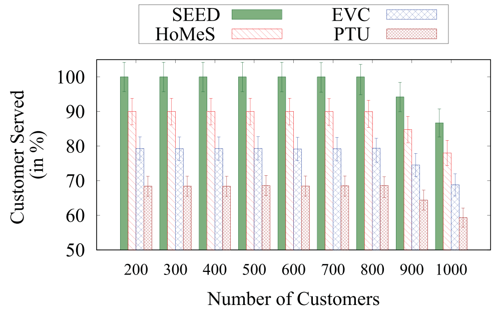

Fig. 3. Percentage of customer served.

2) *Percentage of Customers Served*. The percentage of customers served is calculated as the average value of the percentage of customers served by each micro-grid. With the increase in the number of satisfied customers, the percentage of the customers served increases.
3) *Paid by Customers*. Each customer tries to pay less while consuming a high amount of renewable energy. However, there is a trade-off between the consumed renewable energy and the price paid. Each customer ensures that they pay less per unit of energy while consuming an optimal amount of renewable energy.
4) *Renewable Energy Served by Micro-Grids*. Each micro-grid cannot serve energy more than the amount of generated renewable energy. Therefore, each micro-grid tries to sell the maximum amount of generated renewable energy, while assuring its higher profit.
5) *Profit of Micro-Grids*. Each micro-grid aims to maximize its revenue. In this work, the profit of each micro-grid is calculated as the difference between the earned price by selling requested energy and the total renewable energy generation cost.

5.4 Results and Discussions

For simulation, we assumed that each customer updates the renewable energy request vector and requests energy from micro-grids every 10 seconds.

Figs. 2 and 4 depict the average amount of consumed renewable energy and the corresponding amount paid for renewable energy consumption. From Figs. 3 and 2, we observe that with the increase in the number of customers, the average amount of renewable energy consumed by the customers is reduced. This is because the number of micro-grids is fixed and each micro-grid has a limited amount of

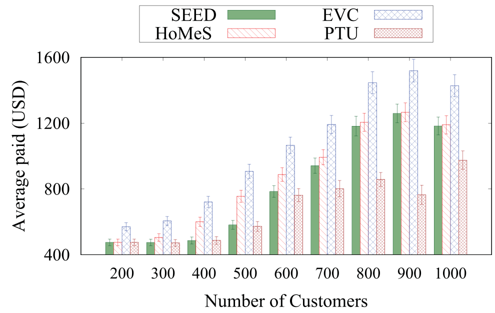

Fig. 4. Price paid by customers.

generated renewable energy. However, with the increase in the number of micro-grids, each customer consumes higher units of energy using SEED, than using the existing schemes such as HoMeS, EVC, and PTU. Therefore, each customer has a higher satisfaction factor using SEED, than using HoMeS, EVC, and PTU. Using SEED, each customer consumes 0.02–0.22 percent, 3.41–13.67 percent, and 8.31–14.05 percent higher amount of renewable energy, i.e., reduction in Co_2 emission, than using HoMeS, EVC, and PTU, respectively. On the other hand, from Fig. 7, we infer that the customers pay 6–29.87 percent lesser using SEED, than using HoMeS and EVC.

Fig. 5 depicts the renewable energy supplied by each micro-grid while varying the number of customers. From Fig. 5, we observe that using SEED, the renewable energy served by each micro-grid is almost similar while considering that the micro-grids have generated a similar amount of renewable energy. Therefore, we claim that the total energy load is properly distributed using SEED, than using HoMeS, EVC, and PTU. From Fig. 5, we observe that the energy-load scheduling among available micro-grids is 18.07–38.92 percent more efficient using SEED, than using HoMeS, EVC, and PTU. From Fig. 6, we observe that using SEED, each micro-grid also charges a similar price per unit of energy. Therefore, the price charged by the micro-grids is reduced by 22.22–35.49 percent using SEED than using HoMeS, EVC, and PTU. Additionally, SEED ensures higher distributed profit for each micro-grid, however, other existing schemes – HoMeS, EVC, and PTU – fail to do so. From Fig. 7, we observe that using SEED, profit earned by each micro-grid is equal and improved by 15.45–58.32 percent than using HoMeS, EVC, and PTU.

6 Conclusion

In this paper, we formulated a sustainable energy management scheme, named SEED, using evolutionary game theory for serving the customers in smart grid. Using the proposed scheme, we observed how each customer decides his/her strategy to request multiple micro-grids, simultaneously, which is not considered in the existing literature. Moreover, SEED ensures that the maximum energy requirement of the customers is satisfied using renewable energy, which, in turn, reduces the carbon footprint. On the other hand, each customer consumes a high amount of renewable energy while paying less. In SEED, each customer decides his/her own renewable energy request vector, and eventually, it leads to an optimal load scheduling among the micro-grids, while reducing the transmission loss in smart

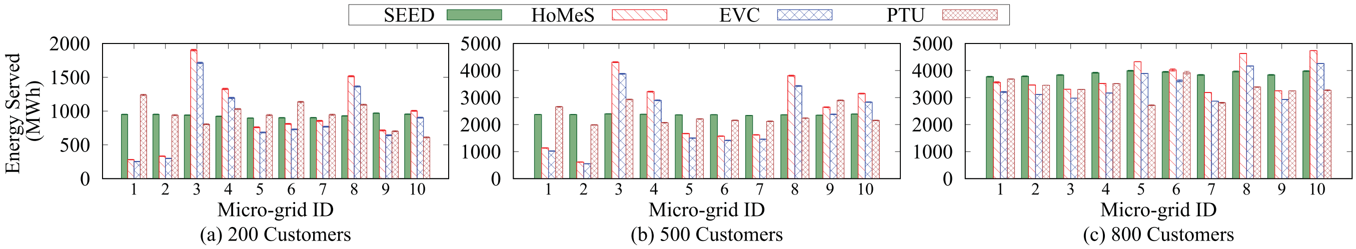

Fig. 5. Renewable energy supplied by each micro-grid.

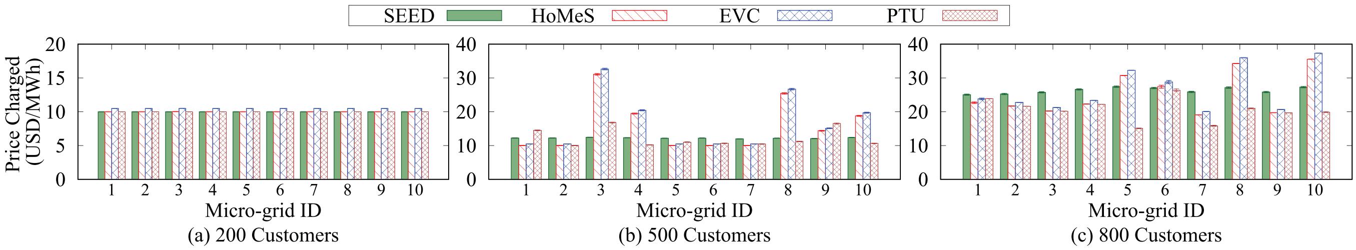

Fig. 6. Price decided by each micro-grid.

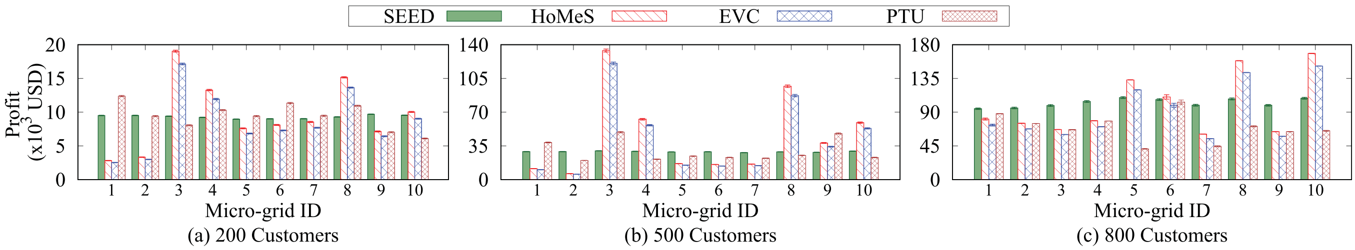

Fig. 7. Profit of each micro-grid.

grid due to energy exchange among the micro-grids and load on the main grid. Further, each micro-grid ensures proper utilization of generated renewable energy with high profit, while considering that the price decided by each micro-grid is dependent on the total requested energy to that micro-grid. Through simulation, we observed that SEED outperforms the existing schemes – HoMeS, EVC, and PTU, in terms of the renewable energy consumed and the price paid by the customers, and the satisfaction and the profit of the micro-grids.

Future extension of this work includes studying how energy management can be improved while ensuring proper energy distribution in the presence of faultiness in a micro-grid or a set of micro-grids. Additionally, this work can be extended to understand the renewable energy distribution mechanism in the presence of misbehaving micro-grids and customers.

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