Dynamic Price-Enabled Strategic Energy Management Scheme in Cloud-Enabled Smart Grid

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***Abstract*—In this work, the problem of high-quality energy service provisioning in the presence of competitive prosumers and micro-grids in cloud-enabled smart grid is studied. Oligopolistic prosumers behave non-cooperatively and store the excess generated energy for future use, which increases the load on the main grid and degrades the performance of the smart grid. To address this issue, we propose a dynamic cloud-based pricing scheme, named SmartPrice, to enforce cooperation among the prosumers for ensuring high quality of service provided by the micro-grids. In SmartPrice, using cloud infrastructure, each micro-grid calculates a reward factor for each prosumer based on his/her behavior to enforce cooperation among them. We model the interaction between each micro-grid and the prosumers using a single-leader-multiple-followers Stackelberg game, where the micro-grids and the prosumers act as the leaders and the followers, respectively. Each micro-grid determines the unit energy price to be charged/paid and each prosumer determines the quantity of excess energy to be supplied for ensuring high revenue. Thus, SmartPrice enforces cooperation among the micro-grids and prosumers. Additionally, using SmartPrice, the price for unit energy charged from the prosumers reduces by 23.37-35.63%, thereby ensuring high revenue and the number of prosumers served by the micro-grids increases by 38.19-53.14%.**

***Index Terms*—Smart Grid, Micro-Grid, Cloud, Cooperation Enforcing, Dynamic Pricing, Oligopoly, Game Theory.**

I. Introduction

To acquire high reliability over the existing power system, the conventional energy distribution grid is envisioned to be enhanced with overlaying communication networks, thereby modernizing the traditional electric grid — a term which is coined as the *smart grid* [1]. A cloud-enabled smart grid is a cyber-physical system capable of ensuring the efficient and robust functioning of the electric network with viable energy management models such as generation, transmission, distribution, and usage. In traditional power distribution systems, the main grid, which is a centralized energy generation unit, distributes energy to the prosumer unidirectionally. Additionally, there is no facility such that the prosumers can interact with the main grid in real-time. Therefore, the prosumers pay based on their energy usage after a fixed interval. On the contrary, in smart grid, the modernized energy distribution network is equipped with the facility of bidirectional electricity exchange, and the energy requirement of each small geographical area is served by a single or a group of micro-grids. Additionally, smart grid is equipped with duplex communication and cloud infrastructure to support the communication and computation needs of the system [2]. Therefore, each prosumer can request energy from the micro-grids in real-time using cloud-enabled energy distribution, which is one of the important features of a smart grid.

In a smart grid, micro-grids use renewable sources such as wind, biomass, and solar power for generating energy. Different micro-grids generate variable amounts of energy every hour of the day. Thus, when a micro-grid does not possess an adequate quantity of generated energy, the users requesting its service must experience a significant quantity of delay before getting served. An alternative, in this case, is to seek the service from the main grid, which incurs higher costs to the users. Thus, to prevent energy deficit and reduce costs, the micro-grids often share their surplus energy with other micro-grids to provide service to the users. However, this process of energy transfer also leads to the wastage of energy units, thereby leading to loss. In such situations, the presence of the energy generation capability of the prosumers may help to resolve the issue. However, as the prosumers are rational, they may behave non-cooperatively and decide to store the energy at their-end [3] instead of supplying the excess quantity of energy to the micro-grids. Hence, for ensuring a high quality of service (QoS) of energy management, we need to motivate the prosumers to act in cooperation. However, as per our knowledge, in the existing literature, there is no such scheme that focuses on motivating the prosumers to behave cooperatively while ensuring high QoS provided by micro-grids and revenue of the prosumers.

Therefore, in this paper, we introduce a *dynamic cooperation enforcing pricing* scheme, named *SmartPrice*, for a cloud-enabled smart grid using a single-leader-multiple-followers Stackelberg game. As per our knowledge, no work in existing literature addressed a similar problem in smart grid. For the aforementioned problem, the Stackelberg game is one of the best choices, as the prosumers and the micro-grids are rational, and try to maximize their benefits. Thereby, we argue that the energy market in the cloud-enabled smart grid has similarities with the oligopolistic market. In SmartPrice, each micro-grid acts as the leader and determines the price for the unit quantity of energy to be charged for each prosumer. Additionally, if there is an energy deficiency at the micro-grid end, it decides the quantity of energy to be procured from each prosumer. On the other hand, each prosumer decides his/her optimal strategy

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– cooperation or non-cooperation – based on the price charged to the micro-grids. In SmartPrice, for ensuring high QoS, each micro-grid provides an incentive to the cooperative prosumers in the form of revenue to the prosumers, which influences the prosumers to behave cooperatively. In summary, our primary contributions are as follows:

1) We present a *dynamic cooperation enforcing pricing* scheme (SmartPrice) for the real-time energy consumption of the prosumers in the presence of energy generation and storage capacity at the prosumer-end in cloud-enabled smart grid.
2) We use a single-leader-multiple-followers Stackelberg game for modeling the interaction between the prosumers and the micro-grids through cloud infrastructure. In SmartPrice, each micro-grid and the prosumers act as the leader and the followers, respectively.
3) To obtain the optimal solution, i.e., Stackelberg equilibrium, of the proposed scheme, SmartPrice, we present three algorithms. Initially, each prosumer decides the quantity of energy to be requested to the micro-grid. Thereafter, using the cloud infrastructure, each micro-grid decides the optimal price to be charged to each prosumer. If the micro-grid requires energy, it requests the prosumers having surplus energy and decides the amount to be procured from cooperative prosumers. On the other hand, using the third algorithm, each prosumer decides his/her strategy of whether to cooperate or not.

The organization of the rest of the paper is as follows. In Section II, we briefly present the existing works focusing on the area of pricing and distributed energy management in smart grid and identified the lacuna in the existing works. The system model considered in this work is discussed in Section III. Section IV describe the modeling of the proposed SmartPrice scheme. We analyze the simulation results of the proposed scheme in Section V. Finally, we conclude the paper while citing the future research directions in Section VI.

II. Related Works

In the past few years, several researchers worked on proposing different schemes for smart-grid, viz., [3]–[13]. We discuss some of these works here. Bakker *et al.* [5] designed a dynamic energy distribution scheme considering economic infrastructure. They designed it as a congestion game. Zaman *et al.* [14] studied the problem of the existence of multiple Nash equilibrium in the electricity distribution market using a co-evolutionary approach. Barabadi and Yaghmaee [15] considered a predetermined base price and proposed a pricing scheme using utility and prospect theory. The authors observed that their proposed scheme enforce the customers to follow the desired norm curve. In another work, a dynamic pricing scheme for PHEVs comprising of two components – local price and roaming price – was proposed by Misra *et al.* [6]. In another work, Neeraj *et al.* [16] proposed a coalitional game-based energy management scheme for PHEVs in smart grid. Jiang *et al.* [17] designed a pricing scheme for the blockchain-enabled smart grid using Stackelberg game with non-cooperative entities. The concept of pricing according to different timings, i.e., on-peak and off-peak hours, was explored by Erol-Kantarci and Mouftah [8] and Molderink *et al.* [7]. In this work, the authors designed an energy management scheme where customers are required to pay higher charges to get instantaneous service. Irtija *et al.* [18] considered that the prosumers are cooperative and proposed a contract-theory based energy distribution scheme. Ajula *et al.* [19] proposed an energy management scheme for distributed data centers using renewable energy in smart grid. The authors also evaluated the optimal allocation of data center resources for processing energy requests. In another work, Ali and Hassanein [20] proposed an energy consumption management scheme for the wireless sensor networks in smart greenhouses, while using a learning algorithm. On the other hand, Vamvakas *et al.* [21], [22] proposed a machine learning-based power allocation scheme while characterizing the service providers in terms of price and service reputation. Chen *et al.* [23] proposed a pricing scheme for the customers having flexible appliances. They also studied the effect of storage devices at the customer end.

Abido [24] proposed a multi-objective optimization problem for the conventional energy distribution grid. In this work, the author ensured a trade-off between the economic and environmental impacts, while considering that fuel combustion, i.e., a non-renewable energy resource, is used to generate the energy. In another work, Bunn and Oliveira [25] considered the presence of multiple energy suppliers. In the presence of traders, each prosumer is mapped to a supplier. Additionally, the authors ensured the balance between the quantity of energy generated by the supplier and the quantity of energy requested by the customers using agent-based computational methods. In another work, Sun *et al.* [26] proposed an optimal cluster formation scheme for intentional islanding in smart grid using the deep learning method. The proposed scheme ensures low power imbalance and stable clusters. Baek *et al.* [27] proposed a security-aware energy management scheme in smart grid. The authors explored different security techniques such as identity-based encryption, signature, and proxy re-encryption. Furthermore, Paudel *et al.* [28] and Misra *et al.* [29], Huang *et al.* [30], and Anoh *et al.* [31] proposed different energy management schemes for peer-to-peer energy trading using evolutionary, coalition, and Stackelberg games, respectively. Similarly, Tushar *et al.* [32] and Han *et al.* [33] also proposed cooperative game-based peer-to-peer energy management schemes in smart grid. On the other hand, Farzan *et al.* [10] explored the idea of predicting energy usage of customers based on the analysis of historical data (for long-term) and adaptive model (short-term) and proposed a distributed energy management scheme. Souza *et al.* [34] analyzed the feasibility of integrating wireless sensor networks for verifying the installation of smart meters in smart grid. In another work, Avancini *et al.* [35] designed an IoT-enabled smart meter for efficient distributed energy management, while ensuring continuous monitoring of the home appliances. Kamyab *et al.* [11] proposed an energy distribution scheme for smart grids with multiple suppliers and consumers. The authors explored two non-cooperative schemes – central price decision by the service provider and distributed load profile decision by

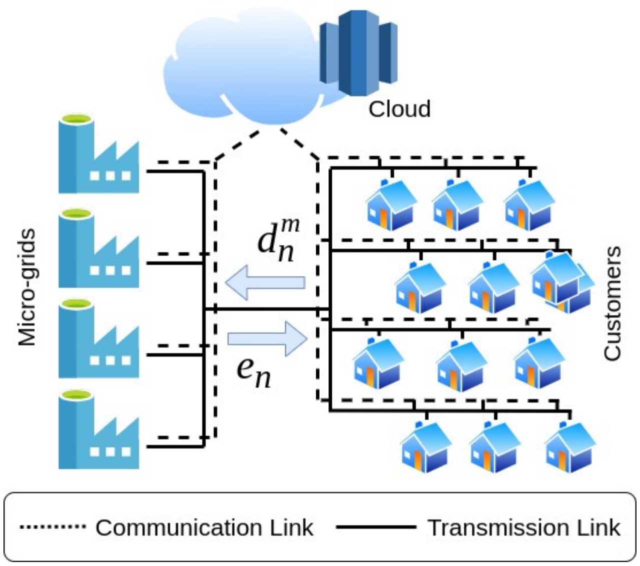


Fig. 1: Schematic Diagram of Cloud-enabled Smart Grid

customers. Mediwaththe *et al.* [13] studied the advantages of the presence of energy generation units with the customers, which enable them to supply excess energy to the centralized energy storage. Another game-theoretic scheme was proposed by Samadi *at al.* [12] in which the authors explored the possibility of sharing excess generated energy between the micro-grids and the customers for maximizing the profit of the customers. Similarly, energy management schemes using cooperative and non-cooperative games and genetic algorithms are proposed by Wang *et al.* [36]. Lokeshgupta and Sivasubramani [37] designed a cooperative game theory-based home energy management scheme for smart grid. Instead of energy generation units, Mondal *et al.* [3] proposed the presence of energy storage units with the customers which help them to store surplus energy for future use.

Synthesis: In the existing literature, researchers proposed several pricing schemes for load distribution to ensure high QoS. Additionally, there are a few schemes proposed in the existing literature which take into consideration the energy storage facility. In these works, the authors claimed that the stored energy can be used by the respective customer as per their needs. Thus, using the existing energy management schemes, the prosumers behave non-cooperatively, and the QoS of energy supplied by the micro-grids degrades significantly. Hence, in this work, we introduce a dynamic cooperation-enforcing pricing scheme in the presence of cloud infrastructure while satisfying the energy requirement of the prosumers. Additionally, we ensure that the prosumers, who are willing to cooperate for enhancing the QoS, get an incentive, which eventually motivates the other non-cooperative prosumers to cooperate.

III. System Model

In this work, a cloud-enabled energy management system comprising of multiple prosumers and micro-grids is considered, as shown in Figure 1. The energy demand of the prosumers is served by the micro-grids and the main grid

TABLE I: List of Symbols

Symbol	Description
$\mathcal{M}$	Set of micro-grids
$\mathcal{N}$	Set of prosumers
$\mathcal{N}_m$	Set of prosumers connected with micro-grid m
$G_m(t)$	Energy generated by micro-grid m
$X_m(t)$	Energy requested to micro-grid m
$S_m(t)$	Energy required by micro-grid m
$g_n(t)$	Energy generated by prosumer n
$x_n(t)$	Energy required by prosumer n
$e_n(t)$	Energy requested by prosumer n
$\mathcal{B}_n(\cdot)$	Utility function of each prosumer n
$\mathcal{U}_m(\cdot)$	Utility function of each micro-grid m
$r_n(\cdot)$	Reward factor of prosumer n
α	Reward controlling factor
$\beta_n^c(t)$	Cooperation index of prosumer n
γ_m	Energy generation cost for micro-grid m
$p_m^n(t)$	Price per unit energy for each prosumer n
$p_m^b(t)$	Base price per unit of energy
$p_m^{v,n}(t)$	Variable price per unit of energy
$p_m^{n*}(t)$	Optimum price charged by micro-grid m
$c_m^{n*}(t)$	Optimum price paid to prosumer n
$d_n^{m*}(t)$	Optimum energy supplied by prosumer n

[38]. In other words, each prosumer is associated with a single micro-grid, and each micro-grid serves a single geographical region. However, to reduce the energy load on the main grid, each micro-grid along with the prosumers aims to ensure that the energy requirement of the prosumers is fulfilled. On the other hand, we consider that each prosumer and micro-grid are capable of generating energy and enabled with a storage facility. Therefore, we assume that the prosumers having surplus energy either store the energy at their end or supply the energy to the micro-grid, which requires energy. We consider that based on these choices, the prosumers are divided into two categories — *cooperative* and *non-cooperative*.

The cooperative prosumers are willing to give back the excess energy to the micro-grid which can be supplied to the other prosumers. On the other hand, the non-cooperative prosumers behave selfishly and store the excess energy that can be used in the future for their usage. Additionally, we assume that the micro-grids access the information about the energy profile of the associated prosumers using cloud infrastructure, and the prosumers are honest, i.e., they provide correct information to the micro-grids.

Each micro-grid $m \in \mathcal{M}$ serves a set of prosumers which is represented as $\mathcal{N}_m$, where $\mathcal{M}$ represents the set of micro-grids. The set of prosumers are denoted by $\mathcal{N}$, where $\mathcal{N}_m \subseteq \mathcal{N}$. Each prosumer $n \in \mathcal{N}$ has a requirement of $x_n(t)$ quantity of energy. Additionally, we consider that each prosumer n generates $g_n(t)$ quantity of energy at time instant t, where $g_n(t) \geq 0$. Hence, if prosumer n generates a lesser quantity of energy than that of his/her requirement, i.e., $g_n(t) < x_n(t)$, s/he requests to micro-grid m for excess amount energy, i.e., $(x_n(t) - g_n(t))$. On the other hand, each prosumer n having excess quantity of energy, i.e., $g_n(t) > x_n(t)$, may either supply the excess $(g_n(t) - x_n(t))$ quantity of energy to the micro-grid m or store the aforementioned quantity of energy if $(g_n(t) - x_n(t)) \leq S_n$, where S_n denotes the storage capacity available at the prosumer-end. Moreover, considering that $(G_m(t) - \sum_{n \in \mathcal{N}_m} x_n) < 0$, the micro-grid m requests $\mathcal{N}_m$ set of prosumers to supply the deficient quantity of energy. The micro-grids also supply energy to the cooperative prosumers in low price as an incentive for cooperation. Thereby, based based on the behavior of the prosumers — cooperative and non-cooperative, the selling price of energy is decided by the micro-grids. As the cooperative prosumers help the micro-grid to reduce the load on the main grid, the micro-grids need to ensure that the cooperative behavior is rewarded over non-cooperative behavior to motivate the prosumers to behave cooperatively. The list of symbols is presented in Table I.

IV. SmartPrice: The Proposed Dynamic Cooperation Enforcing Pricing Scheme

In SmartPrice, the interaction among the micro-grids and the connected prosumers in the cloud-based smart grid is modeled using a single-leader-multiple-followers Stackelberg game [39]–[41]. Each micro-grid, acting as the leader, utilizes the cloud infrastructure to determine the price of unit energy supplied to the prosumers while ensuring that the generated energy is maximally utilized. Additionally, the micro-grids, having deficient energy, determine the quantity of energy to be procured from the prosumers. On the other hand, the prosumers act as the followers and determine the quantity of energy to be procured from the micro-grids. Additionally, the prosumers also determine their behavioral preference – cooperative or non-cooperative, when the micro-grids have a deficit of energy due to less quantity of energy generated[1]. Based on the behavioral strategy of each prosumer, the micro-grids calculate the reward factor using cloud infrastructure, as discussed in Section IV-A, and accordingly determine the price for the unit quantity of energy. We also discuss the justification for using Stackelberg game theory in the subsequent sections.

A. Reward Factor for Cooperation

Motivated by the work of Chakraborty *et al.* [42], we introduce the reward factor for cooperation in demand-based energy distribution system. Initially, each prosumer n has same reward factor $r_n(\cdot)$ which is equal to one, i.e., $r_n(0) = 1$, $\forall n \in \mathcal{N}$. The reward factors of the prosumers are updated in each iteration by the micro-grids, when the micro-grids have energy scarcity. The reward factor $r_n(t)$ of each prosumer n in iteration t is calculated using *weighted moving average* and is represented as follows:

$$r_n(t) = \alpha f(\beta_n^c(t)) + (1 - \alpha) r_n(t-1) \qquad (1)$$

where α is the reward controlling factor, and $\beta_n^c(t)$ and $f(\cdot)$ are the cooperation index and the mean historical cooperation function, as defined in Definitions 1 and 2, respectively. It is to be noted that if the micro-grids have sufficient energy in an iteration, using SmartPrice, the prosumers are considered to be cooperative.

[1]If the prosumers cannot satisfy the energy requirement of the micro-grids, the micro-grids consume energy from the main grid and fulfill the energy requirement of the prosumers.

Definition 1. *The cooperation index $\beta_n^c(t)$ is a binary variable and is calculated as follows:*

$$\beta_n^c(t) = \begin{cases} 1 & \text{if prosumer } n \text{ is cooperative} \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

Definition 2. *Based on the cooperation index $\beta_n^c(t)$, we calculate the mean historical cooperation factor based on the past h iterations using cloud infrastructure. Therefore, $f(\beta_n^c(t))$ is defined as follows, where $t > 0$:*

$$f(\beta_n^c(t)) = \begin{cases} \frac{1}{t} \sum_{\tau=1}^{t} \beta_n^c(\tau), & \text{if } t < (h-1) \\ \frac{1}{h} \sum_{\tau=t-h+1}^{t} \beta_n^c(\tau), & \text{otherwise} \end{cases} \qquad (3)$$

where h is a constant and controls the change in $f(\beta_n^c(t))$.

We consider that there are two prosumers n_1 and n_2, where n_1 cooperates in each iteration, whereas n_2 behaves non-cooperatively in past one iteration at least. Hence, we have, $f(\beta_1^c(t)) = 1$. However, for prosumer n_2, we have, $f(\beta_1^c(t)) < 1$. Therefore, even if both the prosumers n_1 and n_2 behaves cooperatively in the current iteration, reward factor for prosumer n_1 will be higher than that of prosumer n_2, i.e., $r_1(t) > r_2(t)$.

B. Stackelberg Game: The Justification

To design the dynamic cooperation enforcing pricing scheme, *SmartPrice*, we consider a multi-stage Stackelberg game. Initially, each prosumer determines the quantity of energy to be procured from the micro-grid, while considering the quantity of energy generated at their end. Based on this, the micro-grid determines the energy selling price for each prosumer using the reward factor while ensuring high revenue in the cloud-enabled smart grid. In this scenario, if the micro-grids have a deficient quantity of energy, they request the other associated prosumers with surplus energy. Based on the price charged to the micro-grids and the quantity of required energy, each prosumer, i.e., a follower, having surplus energy decides his/her behavior — cooperate and non-cooperate. The micro-grids also ensure that the prosumers' required energy is supplied. On the other hand, the prosumers having excess energy ensure high revenue. Based on the behavior of the prosumers, the micro-grids calculate the reward factor for each prosumer, which will affect the price for the unit quantity of energy to be procured for each prosumer in the next iteration. Thereby, the proposed pricing scheme leads to an *oligopilostic market*, as the energy requirement of the prosumers is satisfied by the micro-grids in the presence of other prosumers having surplus energy, i.e., the small energy suppliers. Therefore, we use a single-leader-multiple-followers Stackelberg game to model SmartPrice scheme.

C. Game Formulation

In SmartPrice, the interaction between the prosumers and the micro-grids is modeled as a single-leader-multiple-followers Stackelberg game, where each micro-grid is the leader and evaluates the optimum price for the unit quantity of energy for each prosumer while ensuring high revenue in the cloud-enabled smart grid. The prosumers are the followers and determine their behavioral strategies while ensuring high QoS and high revenue. Hence, we design the utility functions for the micro-grids and prosumers in SmartPrice while considering the aforementioned functionalities and the corresponding equilibrium strategies, and the equilibrium solutions are evaluated.

1) Utility Function of Each Micro-Grid: The utility function $\mathcal{U}_m(\cdot)$ of each micro-grid m signifies the revenue earned while ensuring that the energy requirement of the prosumers is fulfilled. We consider that $\mathcal{U}_m(\cdot)$ has two components such as revenue function $\mathcal{R}_m(\cdot)$ and cost function $\mathcal{C}_m(\cdot)$. The utility function $\mathcal{U}_m(\cdot)$ is defined as — $\mathcal{U}_m(\cdot) = \mathcal{R}_m(\cdot) - \mathcal{C}_m(\cdot)$. Here, the payoff of $\mathcal{R}_m(\cdot)$ relies on the requested energy by the prosumers, i.e., $X_m(t)$, the quantity of generated energy $G_m(t)$, the price for unit quantity of energy $p_m^n(t)$ for each prosumer n. We define that $p_m^n(t)$ comprises of two components — *base price* ($p_m^b(t)$) and *variable price* ($p_m^{v,n}(t)$). The payoff of $\mathcal{C}_m(\cdot)$ depends on the quantity of deficient energy $D_m(t)$ and the price $p_n^m(t)$ to be paid to each prosumer n for consuming unit quantity of energy. The different parameters of utility function $\mathcal{U}_m(t)$ are discussed as follows:

a) Quantity of Requested Energy: In SmartPrice, initially, each prosumer n evaluates the quantity of energy to requested $e_n(t)$ based on the quantity of generated energy $g_n(t)$ and required energy x_n. We evaluate $e_n(t)$ as follows:

$$e_n(t) = \begin{cases} x_n(t) - g_n(t), & \text{if } x_n(t) - g_n(t) > 0 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

Hence, the requested energy $X_m(t)$ is defined as follows:

$$X_m(t) = \sum_{n \in \mathcal{N}_m} e_n(t) \tag{5}$$

b) Base price for unit quantity of energy: Based on the quantity of generated energy $G_m(t)$, micro-grid m decides a *base-price* $p_m^b(t)$ per unit of energy, which is defined as follows:

$$p_m^b(t) = \gamma_m + \alpha_m e^{\frac{X_m(t)}{G_m(t)}} \tag{6}$$

where γ_m is the cost incurred by micro-grid m for generating a unit quantity of energy; and α_m is a constant and controls the minimum profit of the micro-grid. The micro-grids need to determine α_m optimally using cloud infrastructure. If the α_m is high, the prosumers having excess energy prefer to store energy for the future. On the other hand, if α_m is low, the revenue of the micro-grid reduces.

c) Variable price for selling energy: In the proposed scheme, SmartPrice, we introduce the variable price, which eventually enforces cooperation among the prosumers. The variable price $p_m^{v,n}(t)$ is influenced by the reward factor of each prosumer. Thereby, we argue that the prosumers having high reward factors eventually pay less for consuming energy. We define $p_m^{v,n}(t)$ as follows:

$$p_m^{v,n}(t) = \phi_m \frac{e_m(t)}{X_m(t)} e^{\pi \frac{1}{r_n(t)+\delta}} \tag{7}$$

where π and δ are constants and $\pi, \delta > 0$. ϕ_m is a constant defined by micro-grid m, such that the following condition is satisfied:

$$\varPhi_m(t) \geq \phi_m \frac{e_m(t)}{X_m(t)} e^{\pi \frac{1}{1+\delta}} \tag{8}$$

where $\varPhi_m(t)$ signifies the marginal revenue earned by micro-grid m. Therefore, for consuming unit quantity of energy, each prosumer n needs to pay $p_m^n(t)$, defined as follows:

$$p_m^n(t) = p_m^b(t) + p_m^{v,n}(t) \tag{9}$$

The revenue function $\mathcal{R}_m(\cdot)$ is defined as follows:

$$\mathcal{R}_m(t) = \sum_{n \in \mathcal{N}_m} e_n(t) p_m^n(t) \tag{10}$$

d) Excess Quantity of Requested Energy: Considering the fact that the generated energy $G_m(t)$ is less than the quantity of requested energy $X_m(t)$, each micro-grid m collects the information about prosumers having excess quantity of generated energy using cloud infrastructure and them to supply the surplus quantity of requested energy $S_m(t)$, where $S_m(t) = (X_m(t) - G_m(t))$. We argue that with the increase in $S_m(t)$, the payoff of $\mathcal{U}_m(\cdot)$ of micro-grid m decreases. In each iteration, each micro-grid m identifies the prosumers having an excess quantity of energy by initializing a binary variable $s_n(t)$ with the help of cloud infrastructure. We define $s_n(t)$ as follows:

$$s_n(t) = \begin{cases} 1, & \text{if } g_n(t) > x_n(t) \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

Thereafter, each micro-grid m determines the quantity of energy $d_n^m(t)$ to be requested to each prosumer n, where $s_n(t) = 1$ and $n \in \mathcal{N}_m$, such that the following condition is satisfied:

$$\sum_{n \in \mathcal{N}_m} s_n(t) d_n^m(t) \geq S_m(t) \tag{12}$$

e) Price for the unit quantity of energy Consumption: In SmartPrice, for consuming energy from each prosumer n, each micro-grid m determines the price $c_m^n(t)$ per unit of energy based on the previous reward factor of each prosumer using cloud infrastructure. To enforce cooperation, the micro-grids pay higher to the prosumers with high reward factors. We consider that the micro-grid pays at least $p_m^b(t)$ to ensure the marginal profit of the prosumers. Additionally, similar to the variable price $p_m^{v,n}(t)$ as mentioned earlier, each micro-grid m gives an incentive to the cooperative prosumers by paying $c_m^{v,n}(t)$, defined as follows:

$$c_m^{v,n}(t) = \psi_m \frac{d_n^m(t)}{S_m(t)} e^{\pi \frac{1}{r_n(t)+\delta}} \tag{13}$$

where ψ_m is a constant defined by micro-grid m and $\psi_m < \phi_m$. The cost $c_m^n(t)$ incurred for consuming unit energy from prosumer n is defined as follows:

$$c_m^n(t) = p_m^b(t) + c_m^{v,n}(t) \tag{14}$$

Therefore, we evaluate the cost function $\mathcal{C}_m(t)$ as follows:

$$\mathcal{C}_m(\cdot) = \sum_{n\in\mathcal{N}_m} s_n(t)d_n^m(t)c_m^n(t) \tag{15}$$

Thereby, from Equations (10) and (15), the overall utility function $\mathcal{U}_m(\cdot)$ is defined as follows:

$$\mathcal{U}_m(\cdot) = \sum_{n\in\mathcal{N}_m} [e_n(t)p_m^n(t) - s_n(t)d_n^m(t)c_m^n(t)] \tag{16}$$

In SmartPrice, the objective of each micro-grid is to maximize while optimizing the price $p_m^n(t)$ to be charged for consuming the unit quantity of energy.

2) Utility Function of Each Prosumer: Utility function $\mathcal{B}_n(\cdot)$ of each prosumer n signifies the profit earned by storing energy at his/her end or by selling energy to the micro-grids. Each prosumer n aims to procure energy at less price. Additionally, s/he decides his/her strategy, i.e., storing or selling energy to the micro-grids. Thereby, we consider that the payoff of $\mathcal{B}_n(\cdot)$ depends on the revenue earned by selling $d_n^m(t)$ energy to micro-grid m or paying less for consuming $e_n(t)$ energy from micro-grid m. Therefore, the utility function $\mathcal{B}_n(\cdot)$ needs to satisfy the following properties.

i) Each prosumer n aims to pay less while fulfilling his/her energy requirement. Hence, we argue that, in the proposed scheme, SmartPrice, the cooperative prosumers always have the advantage of paying less while consuming energy.
ii) Each prosumer tries to sell the excess quantity of energy at a high price. In SmartPrice, we ensure that the cooperative prosumers always get a better price for the unit quantity of energy than other prosumers.
iii) To motivate the cooperative prosumers to sell a high quantity of excess energy, we consider the price for the unit quantity of energy increases with the increase in the quantity of energy sold to the micro-grids.

Therefore, the generalized utility function $\mathcal{B}_n(\cdot)$ of each prosumer n is defined as follows[2]:

$$\mathcal{B}_n(\cdot) = d_n^m(t)c_m^n(t) - e_n(t)p_m^n(t) \tag{17}$$

Each prosumer n aims to maximize the payoff of his/her utility function $\mathcal{B}_n(\cdot)$ by optimizing the quantity of energy $d_n^m(t)$ to be supplied to the micro-grid that requires energy. We argue that the decision of the prosumer eventually affects the price charged to/by the micro-grids.

D. Existence of Stackelberg Equilibrium

As discussed earlier, the selling price of energy decided by the micro-grids not only depends on the quantity of energy procured but also depends on the strategy of the prosumer — cooperative or non-cooperative — over the past. In SmartPrice, we consider that the prosumers are rational. Hence, we argue that each prosumer tries to maximize his/her payoff, which leads to a non-cooperative game. However, by introducing the reward factor, SmartPrice aims to ensure a sense of cooperation among the prosumers.

Given the price for the unit quantity of energy decided by each micro-grid, the prosumers determine their optimal strategies, which is considered as the Nash equilibrium strategies of the prosumers. Here, Nash equilibrium signifies that each prosumer cannot ensure a high payoff by choosing other strategies. Based on the strategies of the prosumers, each micro-grid determines the price for the unit quantity of energy, which is considered as the Stackelberg equilibrium. Stackelberg equilibrium symbolizes that there exists an equilibrium amount in the leader-follower hierarchy, as the leader maximizes its payoff, given that the followers have their optimal opinions, i.e., Nash equilibrium strategies. We define the Stackelberg equilibrium of SmartPrice, which replicates an oligopolistic market, as defined in Definition 3. Furthermore, we prove the existence of Stackelberg equilibrium in Theorem 1.

Definition 3. *Stackelberg equilibrium of SmartPrice is defined as* $\langle p_m^{n*}(t), c_m^{n*}(t), d_n^{m*}(t)\rangle$ *while considering the following conditions are satisfied:*

$$\mathcal{B}_n(p_m^{n*}(t), c_m^{n*}(t), d_n^{m*}(t)) \geq \mathcal{B}_n(p_m^{n*}(t), c_m^{n*}(t), d_n^{m}(t)) \tag{18}$$
$$\mathcal{U}_m(p_m^{n*}(t), c_m^{n*}(t), d_n^{m*}(t)) \geq \mathcal{U}_m(p_m^{n}(t), c_m^{n*}(t), d_n^{m*}(t)) \tag{19}$$

where $p_m^{n*}(t)$, $c_m^{n*}(t)$, $d_n^{m*}(t)$ *are the optimum selling price for unit energy by micro-grid* m*, the optimum price charged by prosumer* n*, and the optimum supplied energy by prosumer* n*.*

Theorem 1. *Given the optimal price* $p_m^{n*}(t)$ *and fixed energy requirement of micro-grid* m*, we prove that there exists at least one Stackelberg equilibrium in SmartPrice using variational inequality.*

Proof. In SmartPrice, each micro-grid m aims to maximize its payoff by maximizing the utility function $\mathcal{U}_m(\cdot)$ while obtaining an optimal value of $d_n^m(t)$. Hence, we get that the cumulative objective of the micro-grids is to maximize $\sum_{m\in\mathcal{M}}\mathcal{U}_m(\cdot)$. Hence, using the Lagrangian multipliers with the Karush-KuhnTucker (KKT) condition, we get:

$$\mathcal{L} = \sum_{m\in\mathcal{M}} \mathcal{U}_m(\cdot) - \lambda_1 \sum_m (\sum_n s_n(t)d_n^m(t) - S_m(t)) - \sum_n \lambda_2^n (\sum_m d_n^m(t) - (g_n(t) - x_n(t))) \tag{20}$$

where λ_1 and $\lambda_2^n, \forall n$ are Lagrangian multiplier. Hence, we have the following KKT conditions:

Stationarity: $\nabla_{d_n^{m*}(t)}\mathcal{L} = 0$

Primal feasibility: $(\sum_n s_n(t)d_n^m(t) - S_m(t)) \leq 0$ and $(\sum_m d_n^m(t) - (g_n(t) - x_n(t))) \leq 0$

Dual feasibility: $\lambda_1, \lambda_2^n \geq 0$

[2]Please note that if $e_n(t)$ is positive, $d_n^m(t) = 0$. On the other hand, if $e_n(t) = 0$, $d_n^m(t)$ is a non-negative variable.

Complementary slackness: $\lambda_1 \sum_m (\sum_n s_n(t) d_n^m(t) - S_m(t)) = 0$ and $\lambda_2^n (\sum_m d_n^m(t) - (g_n(t) - x_n(t)) = 0$

By using the property of variational inequality, we get the Jacobian matrix of $\mathcal{L}$, as follows:

$$\nabla_{d_n^{m*}(t)} \mathcal{L} = \begin{bmatrix} -2\frac{\psi_1 d_1^m(t)}{S_m(t)} e^{\frac{\pi}{r_1(t)+\delta}} \\ \vdots \\ -2\frac{\psi_m d_n^m(t)}{S_m(t)} e^{\frac{\pi}{r_n(t)+\delta}} \\ \vdots \\ -2\frac{\psi_m d_{|\mathcal{N}|}^m(t)}{S_m(t)} e^{\frac{\pi}{r_{|\mathcal{N}|}(t)+\delta}} \end{bmatrix} \tag{21}$$

Additionally, we obtain the Hessian matrix of $\mathcal{L}$, as mentioned in Equation (22). From Equation (22), we observe that the Hessian matrix of $\mathcal{L}$ is a diagonal matrix having negative values. Hence, we conclude that there exists at least one Stackelberg equilibrium in SmartPrice. □

Algorithm 1 SmartPrice-I

INPUTS: $g_n(t)$, $x_n(t)$
OUTPUT: $e_n(t)$
PROCEDURE:
1: $e_n(t) = x_n(t) - g_n(t)$
2: **return** $e_n(t)$

E. Proposed Algorithms

In SmartPrice, initially, each prosumer is considered to be cooperative, and the price for the unit quantity of energy, i.e., $p_m^n(t)$ and $c_m^n(t)$, is the same for each prosumer. However, the price for the unit quantity of energy changes over the iterations based on the strategies of the prosumers. The presence of selfish prosumers leads to an oligopolistic market. However, in SmartPrice, the micro-grid motivates the prosumers to behave cooperatively by deciding an optimal price for the unit quantity of energy. We argue that the proposed scheme, SmartPrice, ensures cooperation among the prosumers by executing Algorithms 1, 2, and 3, sequentially. The flowchart of the SmartPrice is presented in Figure 2. Initially, each prosumer n executes Algorithm 1 in order to determine $e_n(t)$. Thereafter, each micro-grid m executes Algorithm 2 and determines $p_m^n(t)$ and evaluates if it needs to procure energy from the prosumers having surplus energy. In case of having a deficient quantity of energy, each micro-grid m requests the prosumers to supply $S_m(t)$ quantity of energy, and determines $c_m^n(t)$ using Algorithm 2. Thereafter,

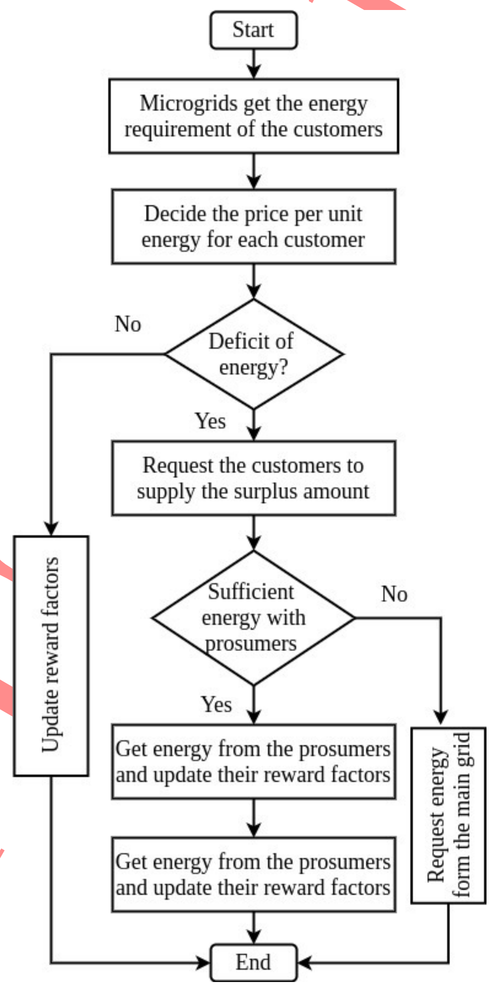


Fig. 2: Flowchart of SmartPrice

each prosumer n executes Algorithm 3 in order to determine $d_n^m(t)$. At the end of an iteration, using Algorithm 2, each micro-grid m updates the reward factor for each prosumer that is to be used in the next iteration.

F. Complexity Analysis

In SmartPrice, the aforementioned three algorithms need to be executed sequentially. Algorithm 1 is executed by each prosumer to decide energy consumption profile and has a time complexity of O(1). Thereafter, Algorithm 2 is executed by each micro-grid and has a time complexity of O($|\mathcal{N}_m|$). Additionally, the time complexity for Algorithm 3 is O(K), where K is a finite value and depends on the constant ρ_n

$$\nabla^2_{d_n^{m*}(t)} \mathcal{L} = \begin{bmatrix} -2\frac{\psi_m}{S_m(t)} e^{\frac{\pi}{r_1(t)+\delta}} & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & -2\frac{\psi_m}{S_m(t)} e^{\frac{\pi}{r_n(t)+\delta}} & \cdots & 0 \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & -2\frac{\psi_m}{S_m(t)} e^{\frac{\pi}{r_{|\mathcal{N}|}(t)+\delta}} \end{bmatrix} \tag{22}$$

Algorithm 2 SmartPrice-II

INPUTS: $e_n(t)$, $s_n(t)$, $r_n(t-1)$, $G_m(t)$ and constants
OUTPUT: $r_n(t)$, $p_m^{n*}(t)$, $c_m^{n*}(t)$
PROCEDURE:

Calculate $p_m^b(t)$
for each $n \in \mathcal{N}_m$ **do**
  Calculate $p_m^{v,n}(t)$
  $p_m^{n*}(t) = p_m^b(t) + p_m^{v,n}(t)$
end for
$S_m(t) = X_m(t) - G_n(t)$
if $S_m(t) > 0$ **then**
  for each $n \in \mathcal{N}_m$ and $s_n(t) = 1$ **do**
    Calculate $c_m^{n*}(t)$
    $d_n(t) \leftarrow$ `SmartPrice-III`$(S_m(t), c_m^{n*}(t))$
    Calculate $\mathcal{U}_m(\cdot)$
    Calculate $r_n(t)$
  end for
  for each $n \in \mathcal{N}_m$ and $s_n(t) = 1$ **do**
    $d_n^{m*}(t) \leftarrow 0$
    do
      $\mathcal{U}_m^{prev} = \mathcal{U}_m(\cdot)$
      Calculate $d_n^m(t)$ while satisfying constraint in Equation 12 and $d_n^m(t) \leq d_n(t)$
    while $\mathcal{U}_m(p_m^{n*}(t), c_m^{n*}(t), d_n^{m*}(t)) \geq \mathcal{U}_m^{prev}$
  end for
end if
return $r_n(t)$, $p_m^{n*}(t)$, $c_m^{n*}(t)$

Algorithm 3 SmartPrice-III

INPUTS: $g_n(t)$, $x_n(t)$, $S_m(t)$, $c_m^n(t)$, ρ
OUTPUT: $d_n^m(t)$
PROCEDURE:

$d_n^m(t) \leftarrow 0$
Calculate $\mathcal{B}_n(\cdot)$
do
  $\mathcal{B}_n^{prev} = \mathcal{B}_n(\cdot)$
  $d_n^m(t) = d_n^m(t) + \rho$
while $\mathcal{B}_n^{prev} < \mathcal{B}_n(\cdot)$
return $d_n^m(t)$

decided by each prosumer n. Hence, the overall complexity of SmartPrice is O($K|\mathcal{N}_m|$).

V. Performance Evaluation

A. Simulation Parameters

To evaluate the performance of SmartPrice, we perform simulations using MATLAB. Generic test-bed information for SmartPrice is given in Table II. We consider a random deployment of micro-grids and prosumers over a geographical area. Within each region [9] of the area, the prosumers are served by a single micro-grid as mentioned earlier. The energy profile of the entities, i.e., micro-grids and the prosumers, are randomly initialized. Additionally, we consider that each prosumer determines her/his energy requirement individually, as shown in Table III. Based on this information, each micro-grid determines the price for the unit quantity of energy to be charged or paid.

TABLE II: System Specification

Parameter	**Value**
Processor	Intel(R) Core(TM) i5-2500 CPU @ 3.30 GHz
RAM	4 GB DDR3
Disk Space	500 GB
Operating System	Ubuntu 16.04 LTS
Application Software	MATLAB 2015b

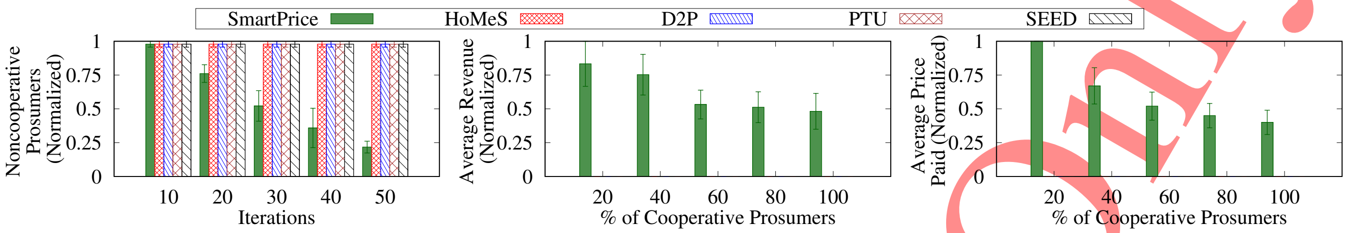
TABLE III: Simulation Parameters

Parameter	**Value**
Simulation area	20×20 km^2
Number of micro-grids	10
Number of Prosumers	1000
Required energy per prosumer	90-100 MWh
Generated energy per prosumer	50-120 MWh
Prosumer's storage capacity	35-65 MWh
Energy generated by micro-grid	500-650 MWh
Generation cost	10-20 USD/MWh

B. Benchmarks

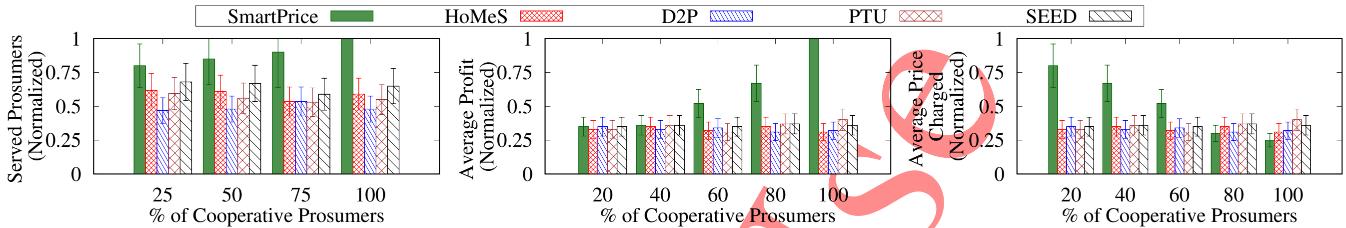
We used three different existing schemes as benchmarks – *home energy management with storage* (HoMeS) [3], Dynamic Pricing for PHEV (D2P) [6], *price taking user* (PTU) [43], and *sustainable energy distribution scheme* (SEED) [29].

In HoMeS, Mondal *et al.* [3] used a game-theoretic analysis to study the nature of energy utilization of the prosumers. Here, the authors considered the presence of storage devices at the user end. On the other hand, in D2P [6], Misra *et al.* studied pricing mechanisms for PHEVs, in which both types of pricing schemes - local and roaming - are explored by the authors. In PTU, Samadi *et al.* [43] studied attempted to reduce the energy generation cost of the prosumers and the power consumption to shift load to off-peak hours. Misra *et al.* [29] proposed an evolutionary game-based energy distribution scheme, named SEED, while ensuring that the energy load is distributed optimally within the micro-grids. They considered that the players are non-cooperative. However, these works do not consider the situation where the micro-grid may request the prosumers for energy supply. Additionally, none of these works aimed to enforce cooperation among the prosumers which improves the QoS of the energy supplied. Using the proposed scheme, SmartPrice, the micro-grids ensure that the prosumers evolve over the iteration and behave cooperatively. On the other hand, SmartPrice ensures high QoS in the cloud-enabled smart grid. Thus, while taking advantage of the oligopolistic market scenario, in SmartPrice, we propose a dynamic pricing scheme to enforce cooperation among the prosumers.



(a) Percentage of non-cooperative Cutomers (b) Average revenue earned by the prosumers (c) Average price paid by the microgrids

Fig. 3: Performance Comparison of non-cooperative prosumers, and average revenue earned and price charged by the prosumers



(a) Served prosumers (b) Average profit of the micro-grids (c) Average price charged by the microgrids

Fig. 4: Performance Comparison of served prosumers, and earned profit, and charged price by the micro-grids

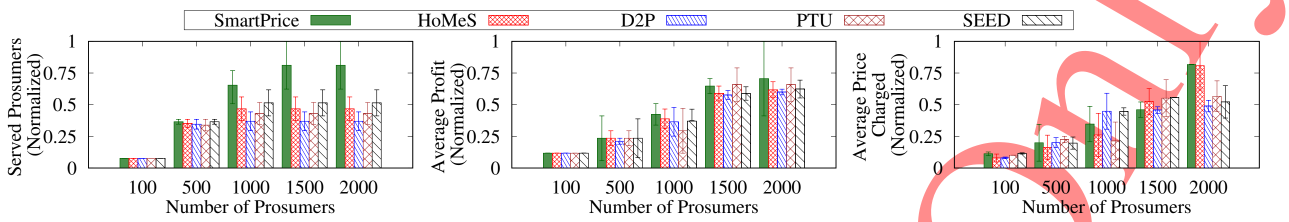
C. *Performance Metrics*

We evaluated the performance of SmartPrice using the following metrics.

1) ***Percentage of Cooperative Prosumers***: In smart grid, we aim to reduce the load on the main grid by serving the prosumers using the renewable energy generated by the micro-grids and other prosumers. Therefore, with the increase in the number of cooperative prosumers, the load on the main grid reduces significantly, thereby improving the QoS.
2) ***Percentage of Served Prosumers***: The percentage of served prosumers indicates the number of prosumers whose energy requests are served successfully by the micro-grids. The increase in the number of prosumers whose energy requirements are satisfied by the micro-grids is, therefore, an indicator of the improvement of the system performance.
3) ***Price Charged by Micro-Grids***: Each prosumer aims to procure energy by paying less price to the micro-grids. The higher quantity of energy procured by a prosumer increases the price charged to the prosumer, for a fixed per unit rate. Thus, each prosumer aims to pay less price for consuming energy.
4) ***Price Charged by the Prosumers***: The micro-grids have limited energy generation capacity. Hence, if the prosumers demand energy higher than the generated energy, the micro-grids need to rely on the prosumers having surplus energy. Eventually, the prosumers earn revenue by supplying the excess quantity of energy to the micro-grids.
5) ***Profit of Micro-grids***: The micro-grids try to maximize their earnings to maximize their revenue or profit. The surplus earned by the micro-grids by selling energy after covering its total generation cost determines the profit of the micro-grid.
6) ***Profit of Prosumers***: In SmartPrice, the prosumers having surplus energy get a chance to earn revenue by supplying the excess quantity of energy generated to the micro-grids having deficient energy. On the contrary, the prosumers may behave non-cooperatively and chose to store the excess quantity of energy for future use.

D. *Results and Discussions*

Figure 3(a) shows the variation of the number of cooperative prosumers in the system over time using the schemes — SmartPrice, HoMeS, D2P, PTU, and SEED. We consider that, initially, every prosumer in the system is cooperative. Over time, an increasing percentage of prosumers, driven by their self-interests, determines to store their excess energy for future use instead of selling their energy to micro-grids. This results in the observed initial dip in the percentage of cooperative prosumers. However, after a few iterations, the percentage of cooperative prosumers begins to increase using SmartPrice unlike the other schemes in the existing literature. This is because, as a result of the initial decrease in the percentage of cooperative prosumers, the average price charged to the prosumers by the micro-grids increases. When the price increase becomes significant, the prosumers are motivated to behave cooperatively to facilitate the reduction of the cost of purchasing unit energy from the micro-grids. Thus, the percentage of cooperative prosumers in the system increases with time. However, this is not the case for the other existing schemes, where the behavior of the prosumers does not influence the market price of energy. Hence, we argue that SmrtaPrice enforces cooperation among the prosumers in the cloud-enabled smart grid. From Figure 4(a), we yield that with the increase in the number of cooperative prosumers, the QoS, i.e., the number of served prosumers, increases. Similarly, with the increase in the number of prosumers, the served prosumers increases initially. However, due to the limitation



(a) Served prosumers (b) Average profit of the micro-grids (c) Average price charged by the microgrids

Fig. 5: Performance Comparison of served prosumers, and profit earned and price charged by the micro-grids with 50% cooperative prosumers.

of generated energy, the number of served prosumers gets saturated eventually. Moreover, it is to be noted that using SmartPrice, the remaining prosumers are served from the main grid. We did include them in the Figure 5(a).

Figures 3(b) and 3(c) depict the variation in the average price for the unit quantity of energy charged by each micro-grid to the prosumers with the increase in the percentage of cooperative prosumers in the system. Figure 3(b) shows that using SmartPrice, the price for the unit quantity of energy charged to the prosumers decreases by 23.37-35.63% with the increase in the percentage of cooperative prosumers, unlike the existing schemes — HoMeS, D2P, PTU, and SEED. This is because using SmartPrice, the cooperative behavior of prosumers is rewarded by reducing the cost per unit of energy. Thus, the cooperative prosumers pay less price for the unit quantity of energy, thereby reducing the average price charged to the prosumers by the micro-grids. On the other hand, using the existing schemes, the price charged to the prosumers is independent of their behavior. Thus, the average price charged continues to remain higher irrespective of the increase in the cooperation by the prosumers. Additionally, it is to be noted that the existing works do not consider the situation where the micro-grid may request the prosumers for energy supply. Therefore, from Figures 3(b) and 3(c), we observe zero contribution in the revenue earned and the price charged by the prosumers using the existing schemes — HoMeS, D2P, PTU, and SEED. Moreover, with the increase in the number of prosumers in the system, the average price charged to the prosumers decreases further using SmartPrice. On the other hand, as shown in Figure 4(c), SmartPrice ensures high revenue for the micro-grids, as the prosumers served by the micro-grids increase by 38.19-53.14%. We also observe a similar trend in Figure 5(b). Additionally, we observe that using SmartPrice, the profit of the micro-grids is always higher than using the existing schemes, as SmartPrice ensures a high number of prosumers are served and high utilization of the generated energy.

Similarly, in Figure 4(b), we observe the variation of the price charged to the micro-grids by the prosumers with the increase in the percentage of cooperative prosumers in the cloud-enabled smart grid. We yield that the price charged to the micro-grid by the prosumers for unit energy increases with the increase in the percentage of cooperative prosumers using the proposed scheme, SmartPrice. However, the revenue earned by the prosumers using other existing schemes is significantly low, as these schemes do not consider the involvement of the prosumers in energy supply along with the micro-grids. This is also because using SmartPrice, prosumers are encouraged to sell their excess energy to the micro-grids by paying them a higher price for the unit quantity of energy. Moreover, with the increase in cooperative prosumers, each micro-grid is presented with the option of purchasing energy from a higher number of prosumers. Thus, the average revenue of prosumers increases as depicted in Figure 4(c). On the other hand, with the increase in the number of prosumers, the average price charged by the micro-grids increases, as depicted in FIgure 5(c). This is because the energy demand increases with the increase in the number of prosumers, however, the amount of generated energy remains fixed. Therefore, we argue that the proposed scheme, SmartPrice, enhances the performance of energy management, i.e., enhances the QoS of energy supply, while ensuring high revenue earned by the micro-grids and the prosumers. Additionally, SmartPrice ensures cooperation among the prosumers, which also eventually enhances the QoS of the energy supply.

Therefore, we yield that SmartPrice enforces cooperation among the prosumers by introducing the reward to be awarded by the micro-grids and ensures high revenue of the micro-grids. We also observe that the percentage of cooperative prosumers in the system increases with time using SmartPrice, which in turn reduces the price to be paid by the prosumers as well as the micro-grids, which results in high QoS using SmartPrice than using the existing schemes.

VI. Conclusion

In this paper, we studied the problem of cloud-enabled efficient energy management in the presence of energy generation capacity at the prosumer-end using a single-leader-multiple-followers Stackelberg game. Using the proposed scheme, SmartPrice, we observed that the micro-grids ensure cooperation among the prosumers. In SmartPrice, using the cloud infrastructure, the micro-grids determine the optimal price for the unit quantity of energy to be charged from the prosumers and paid to the prosumers, respectively. On the other hand, we observed that the prosumers, who are non-cooperative by virtue, are motivated by the micro-grids to act cooperatively, thereby ensuring the high QoS. The simulation results indicate that the proposed scheme, SmartPrice, performs superior compared to the existing benchmark schemes.

This work can be extended in the future by studying the nature of the energy distribution while introducing a bidding strategy so that the prosumers also have active participation in deciding the price for the unit quantity of energy. This work also can be extended while introducing a broker in between the micro-grids and the prosumers. This broker may act as a third-party entity that ensures the anonymity of the prosumers.

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