PETS: P2P Energy Trading Scheduling Scheme for Electric Vehicles in Smart Grid Systems

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***Abstract*— Due to the lack of improper access control policies and decentralized access controllers, security and privacy-aware peer-to-peer (P2P) energy trading among electric vehicles (EVs) and the smart grid is challenging. Most of the solutions reported in the literature for P2P energy trading are based upon centralized controllers having various security flaws resulting in their limited applicabilities in real-world scenarios. To handle these issues, in this paper, we propose a P2P energy trading scheduling scheme called as P2P Energy Trading Scheduling *(PETS)* using blockchain technology. PETS is based on real-time energy consumption monitoring for balancing the energy gap between service providers (SPs), *i.e.,* smart grids and service consumers, *i.e.,* EVs. In PETS, the Stackelberg game theory-based 1-leader multiple-followers scheme is proposed to depict the interactions between EVs and the SP. The selection of the leader among all SPs is made using a second-price reverse auction. As per the announced energy price by the leader, EVs manage energy consumption by minimizing their energy bills. In PETS, on the leader's side, we propose the Genetic algorithm to maximize its profit. In contrast, on the followers' side, *i.e.*, EVs, we use the Stackelberg Equilibrium to minimize their energy bills. Simulation results demonstrate that the proposed PETS scheme outperforms the existing state-of-the-art schemes using various performance evaluation metrics. Specifically, it reduces the peak-to-average ratio (PAR) by 12.5% of EVs' energy load in comparison to the existing state-of-the-art scheme.**

***Index Terms*— P2P energy trading, scheduling, Stackelberg game, genetic algorithm, electric vehicles, real-time pricing.**

NOMENCLATURE

EV_j	Electric vehicles.
SP_L	Service provider as leader.
N	Number of SPs.
n_i	Number of EVs.
p^h	Energy price in h hours.
$p^{min,max}$	Minimum and maximum price by the SP_L.
$h \in H$	Time in hours.
$X_{j,EV}$	Scheduling vector of energy consumption of each EV.
$\gamma_{j,EV} \in H$	Beginning time.
$\beta_{j,EV} \in H$	End time.
$\alpha_{j,EV}^{min,max}$	Minimum and maximum energy needed for consumption.
Bid_i	Auction bid price by SP_i.
Bid_{lowest}	Choose lowest bid from all SPs.
$E_{j,EV}$	Total energy consumption.
$Price()$	Energy pricing scheduling for charging the EVs.
$Energy_h^{max}$	Maximum load capacity of SP_L.
P_h	Amount of energy provided in time "h".
$Cost_h$	Cost of giving energy by SP_L.
S_L	Strategy space of SP_L.
S_{F_j}	Strategy space of EV_j.
R_{F_j}	Best response of EVs.
J_L	Pay function of SP_L.
J_{F_j}	Utility function for EVs.
$f(\bar{x})$	Penalty function.
$length_b$	Length of binary bits.
R_c	Crossover rate.
R^n	Real numbers.
m	Total constraints.
s	Non-violated constraints.
P_{Peak}	Peak load of EVs.
P_{Avg}	Average load of EVs.

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I. INTRODUCTION

THE traditional electric grids face several challenges such as increased energy demands, limited energy resources, expensive energy-generating processes, environmental pollution by the emission of CO_2, and grid instability [1]. These challenges create issues on the power grid's scalability and reliability, which in turn have Quality-of-Service (QoS) and Quality-of-Experience (QoE) degradation for the end-users. However, this conventional power grid system is improved by the integration of distributed energy resources (DERs) with efficient demand-side management (DSM) programs [2]. DSM programs are used for planning and monitoring the activities of electric utilities to control and manage the energy consumption at the end-users side [3], [4]. These programs have reliable, secure, and efficient grid operations for the future smart grid [5]. For example, real-time pricing changes quickly in the energy trading market. Also, the usage and deployment of EVs in the smart grid can increase the importance of DSM programs because EVs consume and store energy in their batteries to share with the other EVs or the grid to create an eco-friendly environment. They operate on an electric motor, which needs energy generated from renewable resources instead of an internal combustion engine that needs fuel and coal (non-renewable). As mentioned in the report [6], *J.P. Morgan* estimates that approximately 8.4 million EVs will be on road across the globe by 2025. Therefore, it is challenging to balance the energy demands of EVs in peak hours with the existing DSM programs in the smart grid systems [7]. Hence, there is a requirement of a reliable energy trading scheme between EVs and the SPs to furnish the future energy demands of EVs.

There are direct and indirect methods to control the energy demands of EVs [8]. In the direct method, SPs control and maintain the energy load based on the contract with the end-users. It is the easiest method to control and manage the energy demands, but there are some security and privacy issues in it. In contrast, the indirect method is applied to different energy prices during a particular day. In this method, EVs can reduce their energy demands by deviating their negotiated load into lower energy price hours such as time-of-use (ToU) and real-time pricing. However, it is difficult to handle the negotiated load of EVs in off-peak hours with current energy trading scheduling schemes. So, in such a scenario, peer-to-peer (P2P) energy trading scheduling can provide a unique solution to buy and sell energy between EVs and the SPs in this scenario [9]. It consists of direct energy trading between EVs and the SPs such that energy from DER is traded between EVs and the SPs. However, sometimes EVs may not participate in buying energy in the P2P network due to leakage of their private information among peers in the network, which may create imbalance of the energy gap. Moreover, the security and privacy of the existing DSM programs is critical as energy exchanges between EVs and the SPs are affected by cyber-attacks such as false data injections, manipulation of load profiles of EVs, and energy losses in smart grid systems [10]. Several researchers discussed the security and privacy issues of EVs in smart grid systems. Hence, they classified attacks based on integrity, availability, accountability, and confidentiality. Moreover, the existing proposals mainly focus on cyber-attacks or protecting some particular components in smart grid systems based on various centralized controllers having single point of failure. So, to handle the security and privacy preservation of EVs in smart grid systems, there is a need to design a distributed mechanism to provide efficient energy exchanges between EVs and the SPs. In addition, P2P energy trading must meet the requirements for security (prevent from adversaries, identity-preservation of EVs), reliability (preventing data manipulation, no information leakage), and scalability (to participate more EVs in the P2P energy trading). Hence, designing a distributed P2P energy trading scheduling ensures privacy and security to EVs can be possible by the usage of *“Blockchain Technology”* [11]. It provides a secure platform for EVs in P2P energy trading without the intervention of centralized controllers. Also, EVs can directly connect with the SPs for energy exchanges with privacy preservation to ensure data immutability and transparency [12], [13]. From the aforementioned discussions, in this paper, we propose the PETS scheme between EVs and the SP using blockchain technology.

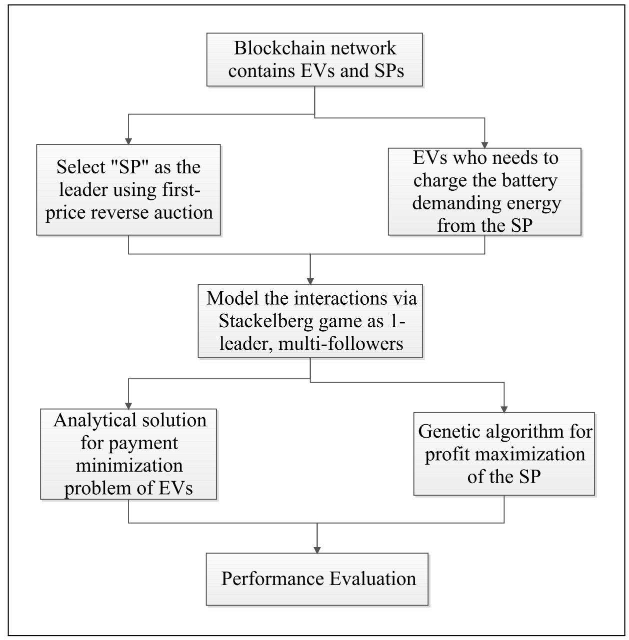

Fig. 1. Schematic overview of PETS scheme.

A. Motivation

EVs play a vital role to balance the demand and supply for energy trading in smart grid systems. While several conventional energy trading solutions are present, such as centralized key management schemes but a key limitation in many of these solutions is the single point of failure. The trusted third party can be targeted and successfully compromised by the attacker, including a malicious insider. To address these challenges, we state the potential of distributed secure energy trading scheme in smart grid systems. The benefits of blockchain technology are low transaction costs, faster transactions, transparency, and immutability that have attracted attention from researchers in different domains and for different applications. It provides a transparent solution, where any changes to the blockchain or the transaction received in the public wallet address are globally displayed by all communication parties. Such changes are immutable, which means that the transactions cannot be deleted or changed. Hence, we propose a decision-making scheme based on Stackelberg game theory for EVs and the SPs using blockchain technology. We propose a second-price reverse auction to select the leader among all SPs and model the interactions with EVs using the Stackelberg game as 1-leader, multi-follower. In addition, we present the analytical solution for payment minimization of EVs and the Genetic algorithm for profit maximization of SPs. Fig. 1 outlines the schematic overview used to reach the objectives of PETS scheme.

B. Contributions

Following are the main contributions of this paper.

- We propose a P2P energy trading scheduling, *i.e.,* PETS framework using blockchain for real-time energy consumption between EVs and the SPs.
- A theoretical game-based model is proposed to explore the interactions between EVs and the SP in smart grid systems. We used a second price reverse auction to select the leader among all SPs. Then, we presented the Stackelberg game theory scheme as a 1-leader, multi-followers, where SP is the leader and EVs are followers.
- Lastly, we use the Genetic algorithm to find the Stackelberg solution in smart grid systems. Simulation results show the reduced energy bills of EVs and profit maximization of SPs.

C. Organization of the Paper

Rest of the paper is organized as follows. Section II discusses the summary of related work. The system model is discussed in Section III. Section IV presents the proposed PETS scheme. Simulation results and performance evaluation are discussed in Section V. Finally, the paper is concluded in Section VI.

II. Related Work

In this section, we review the related work for P2P energy trading in smart grid systems. Many research articles proposed by the researchers for P2P energy trading into several sectors [14]–[19] such as micro-grid [20], EVs [21], and distribution networks [22].

Alam *et al.* [23] proposed a P2P energy trading model for smart homes in the smart grid. They considered the Pareto optimality to optimize and minimize the total energy cost of the system. Aznavi *et al.* [24] proposed a P2P energy trading model between EVs and the entities equipped with solar energy generation. They used the dynamic pricing mechanism to increase the owner's profit. Their simulation results show a reduction of 23.24% in the total cost of prosumers. Nguyen *et al.* [25] proposed a decentralized P2P energy trading mechanism having EV-wireless charging-discharging lanes. They described a privacy-preserving consensus protocol for desired energy price and amount of EVs. Zhang *et al.* [26] proposed joint energy trading and uncertainty in the energy market. Their simulation results balance the photovoltaic forecast error by 55.3% locally. Tushar *et al.* [27] proposed a coalition game-based P2P energy trading and mid-market rate pricing mechanism to ensure stability in the smart grid. Similarly, Tushar *et al.* [28] proposed a P2P auction mechanism for energy trading where the authors shared the storage of energy between the shared facility controllers and the community. Leong *et al.* [29] proposed a bidding strategy based on a Bayesian game to ensure fair bidding in P2P energy trading. Similarly, Faqiry *et al.* [30] proposed a double auction mechanism to protect users' private information in P2P energy trading. They optimized the social welfare problem where buyers aim to minimize their energy price and sellers aim to maximize their energy consumption. Chai *et al.* [31] proposed a Stackelberg game for P2P energy trading to maximize the participants' benefits. Similarly, Paudel *et al.* [32] proposed a Stackelberg game model to find the interaction between the utility companies and end-users to maximize the benefits of both. Zhou *et al.* [33] proposed a pricing methodology for electric vehicle chargig stations for the consumption of renewable energy. The selection of Charging stations by the EVs is based on charging price, distance and traffic congestion information. Similarly, Amini *et al.* [34] proposed a distributed consensus and innovations approach for optimal charging of plug-in EVs in transportation electrification networks. Aggarwal *et al.* proposed a demand-response management scheme for energy trading between EVs and the SPs to maximize the social welfare maximization [35].

However, despite using P2P energy trading, the above-mentioned implementations [29], [31], [32], [36] do not provide a secure platform to share data and energy among peers. Therefore, there is a possibility of leaking peers' personal information and compromising the system's reliability. To address these security problems, we propose a P2P energy trading scheduling, *i.e.,* PETS scheme using blockchain technology. It is a distributed ledger technology (DLT) where transactions are recorded securely in a decentralized way. It provides immutability, transparency, privacy, and security to smart grid systems. Once the transactions are recorded on a blockchain, there is no possibility of tampering with the transactional data secured by cryptographic primitives [37]. From these advantages, researchers have used this technology in P2P energy trading in various sectors [12] such as intelligent transportation [38], [39], vehicle-to-grid (V2G) [40], [41], smart grid [42], [43], and smart homes [44] to maintain transparency and trust in energy trading [45]. They designed the smart contracts on the Ethereum platform for defining the energy trading logic, including the auction mechanism [46], [47], game theory [48]–[53], bargain theory [54], and incentive contract theory [55]. Li *et al.* used the improved krill herd algorithm to solve a mixed-integer programming-based problem between EVs and power grids in energy trading. They implemented the proposed model on Hyperledger Fabric and evaluated the scalability and performance of the model [56], [57].

From the literature study, we have observed that blockchain technology in P2P energy trading between EVs and the SPs having game theory had not been widely used. Hence, we propose the PETS scheme between EVs and the SPs in smart grid systems. It uses real-time pricing, game theory, and blockchain to manage and optimise P2P energy trading. None of the existing proposals have addressed the real-time pricing of EVs' energy consumption in P2P energy trading. In contrast to the existing proposals, the proposed PETS scheme mainly resolves the following issues (i) minimization of EVs' energy bills, (ii) profit maximisation for SPs, (iii) improvement in scalability issues, and (iv) balance the EVs' energy load with a low PAR value to provide security and privacy the energy transactions between EVs and the SP. The comparative analysis of the proposed PETS scheme with the existing schemes is described as shown in Table I.

TABLE I

COMPARATIVE ANALYSIS OF PETS SCHEME WITH THE EXISTING SCHEMES

References	Contribution	Theory	Optimization method	Block-chain	RTP-based scheduling	Smart contracts	Area
Lasla *et al.* [46]	Blockchain-based energy trading for EVs	Auction theory	-	✓	×	✓	Smart City
Liu *et al.* [47]	EVs-based power trading using blockchain	Reverse Auction theory	-	✓	×	✓	Vehicle-to-Grid
Hasija *et al.* [48]	Lightweight framework for data sharing and energy trading	Directed Acyclic Graph	-	✓	×	✓	Vehicle-to-Grid
Zhang *et al.* [49]	Energy trading on a distributed platform with transmission cost	Game theory	-	-	×	✓	Grid
Jember *et al.* [50]	Energy transmission management in Internet of EVs	Game theory	Contract theory	-	×	-	Vehicle-to-Grid
Ma *et al.* [51]	RTP scheme for energy management	Game theory	Game theory	-	✓	-	Smart energy hub
Anoh *et al.* [52]	P2P energy trading i virtual micro-grids	Game theory	Game theory	✓	×	-	Smart grid
Doan *et al.* [53]	P2P energy trading using blockchain	Game theory	Game theory	✓	×	✓	Smart grid
Ping *et al.* [54]	EVs charging coordination method using blockchain	Alternating direction method of multipliers (ADMM)	Bargain theory	✓	×	-	Electric vehicles
Chen *et al.* [55]	Secure electricity trading for EVs	Game theory	Contract theory	✓	×	✓	Electric vehicles
PETS scheme	P2P energy trading scheduling scheme based on RTP	Auction + Game theory	Genetic Algorithm	✓	✓	✓	Smart grid

III. SYSTEM MODEL

We have divided this section into two parts (i) Blockchain-based P2P energy trading scheduling architecture and (ii) problem formulation.

A. Blockchain-Based P2P Energy Trading Scheduling Architecture

Fig. 2 presents the blockchain-based P2P energy trading scheduling model in smart grid systems, where N is the number of SPs as $SP = (SP_i : \forall i \in N)$ and n_i is the number of EVs as $EV = (EV_j : \forall j \in n_i)$; whereas, $n_i \subseteq N$ and $i, N = (1, 2, \ldots, N)$. The energy information processing network has data processors (DPs) to collect and transmit energy data and act as distribution of nodes on the blockchain network. In the system model, DPs are joined as point-to-point communication in a distributed shared information node and maintain the distributed ledger. Digital signatures are used to provide security and privacy in a real-time P2P energy trading interaction system on a blockchain [37]. It not only assure effective and secure energy trading but also verifies whether the energy trading between EVs and the SP is legal and efficient.

In this model, EV_j wants to buy an energy for charging the battery from SPs. Firstly, SPs, *i.e.,* SP_i submitted a sealed-bid on a blockchain for selling the energy to EVs or to take charge of EVs. Then, using a second-price reverse auction based smart contract [58], the SP having lowest bid among all SPs is selected to make it as the leader, *i.e.,* SP_L is as shown in Algorithm 1. Secondly, to design the energy trading interactions between EV_j and the SP_L, we use Stackelberg game theory having 1-leader (SP_L) and multi-followers (EV_j).

Here, we define SP_L strategy space, *i.e.*, $S_L = (p^1, p^2, \ldots, p^h)$, where p^h represents the energy price in h hours. We also define the $p^{min} \leq p^h \leq p^{max}$, where p^{min} is the minimum price that can be offered by the SP_L and p^{max} is the maximum price that SP_L can offer in $h \in H$ time. On the other hand, the price announced by SP_L must be less than all the other SPs on a blockchain (see Algorithm 1).

Algorithm 1 Selection of the Leader

Input: N: The number of SPs requests for giving the energy to EVs.

Output: SP_L.

```
procedure FUNCTION(N)
    for (i = 1; i ≤ N; i++) do
        Select the SP_i
        Submit the auction bid price Bid_i on the blockchain network
        Select the lowest bid, i.e., Bid_lowest value using second-price reverse auction
    end for
    Make SP_i corresponding to Bid_lowest as Leader, i.e., SP_L
end procedure
```

B. Problem Formulation

1) Optimal Real-Time Pricing Consumption for EVs- At Follower Level: In this section, we define an energy consumption scheduling vector for each EV, *i.e.,* $EV \in EV_j$, $j \subseteq N$. Using this, we can control the hourly use of energy of each EV by defining the energy price. The scheduling vector of energy consumption for each EV is as follows:

$$X_{j,EV} = [x^1_{j,EV}, x^2_{j,EV}, \ldots.., x^h_{j,EV}] \tag{1}$$

where, $h \in H_{j,EV} = (1, 2, \ldots, 24)$ and $x^h_{j,EV} \geq 0$ is the j^{th} EVs' energy consumption at time h. So, the total energy consumption of this EV_j is represented as $E_{j,EV}$. For a valid scheduling interval, an EV needs $h_{j,EV} = (\gamma_{j,EV}, \ldots, \beta_{j,EV})$, where $\gamma_{j,EV} \in H$ is the beginning time and $\beta_{j,EV} \in H$ is the end time. So, to satisfy the energy needs of EVs, we define

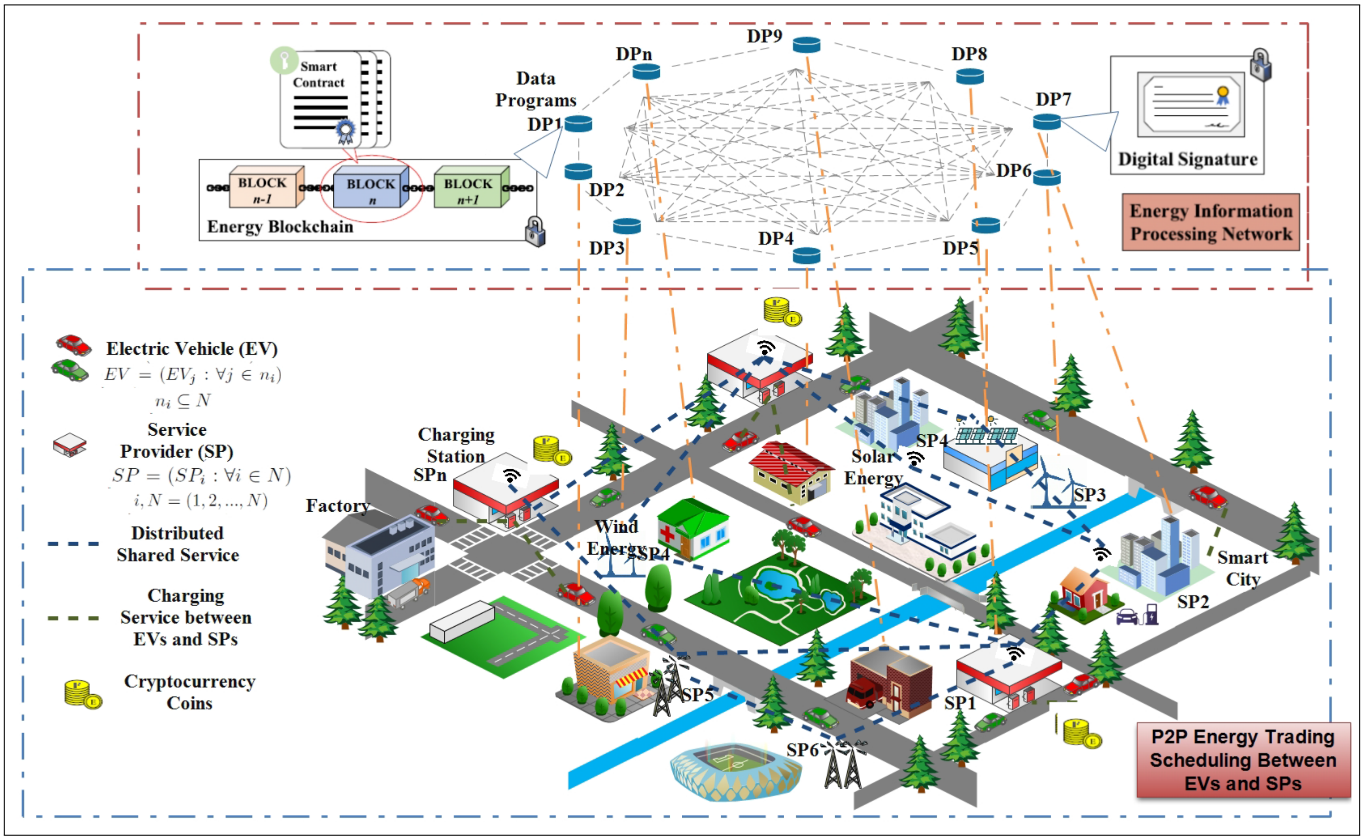

Fig. 2. Blockchain-based P2P energy trading scheduling scenario.

the following:

$$\sum_{h=\gamma_{j,EV}}^{\beta_{j,EV}} x^h_{j,EV} = E_{j,EV} \tag{2}$$

$$x^h_{j,EV} = 0, \quad \forall h \in H_{j,EV} \tag{3}$$

After determining the minimum energy needed $\alpha^{min}_{j,EV}$ and the maximum energy needed $\alpha^{max}_{j,EV}$ of EVs, the energy consumption for each EVs is between:

$$\alpha^{min}_{j,EV} \leq x^h_{j,EV} \leq \alpha^{max}_{j,EV}, \quad \forall h \in H_{j,EV} \tag{4}$$

So, the price optimization of all EVs is computed as follows:

$$\begin{aligned} min\ EV &= min \sum_{h=1}^{H} p^h \times \left(\sum_{EV \in EV_j} x^h_{j,EV} \right) \\ s.t.\ C_1 &: \sum_{h=\gamma_{j,EV}}^{\beta_{j,EV}} x^h_{j,EV} = E_{j,EV}, \\ C_2 &: x^h_{n_i,EV} = 0, \quad \forall h \in H_{j,EV}, \\ C_3 &: \alpha^{min}_{j,EV} \leq x^h_{j,EV} \leq \alpha^{max}_{j,EV}, \quad \forall h \in H_{j,EV} \end{aligned} \tag{5}$$

2) Profit Maximization Model for SPs- At Leader Level: In this section, we define the model for profit maximization of SP_L by using the funds by subtracting the cost of energy charged on SP_L. Firstly, we discuss the cost model and then, profit maximization is discussed. To determine the energy price, we define the cost function of SP_L as $Cost_h(P_h)$ where, $Cost_h$ represents the cost of giving energy by SP_L at time $h \in H$ and P_h represents the amount of energy provided to all EVs in h hour. This function is a convex increasing function for each h in P_h. So, the cost function is defined as follows:

$$Cost_h(P_h) = m_h P_h^2 + q_h P_h + r_h \tag{6}$$

where, $m_h \geq 0, q_h \geq 0, r_h \geq 0$ at each period of hour time $h \in H$.

For each hour $h \in H$, the minimum price and maximum price of the energy that SP_L can offer is represented as $p^{min} \leq p^h \leq p^{max}$ and the maximum load capacity of SP_L is '$Energy^{max}_h$' defined on a blockchain network in h hour is defined as follows:

$$\sum_{n \in N} \sum_{a \in EV_j} x^h_{j,a} \leq Energy^{max}_h, \quad \forall h \in H \tag{7}$$

Then, the profit maximization problem of SP_L is defined as:

$$\begin{aligned} max & \left\{ \sum_{h \in H} p^h \times \sum_{n \in N} \sum_{a \in EV_j} x^h_{j,a} \right. \\ & \left. - \sum_{h \in H} Cost_h \left(\sum_{n \in N} \sum_{a \in EV_j} x^h_{j,a} \right) \right\} \\ s.t.\ C_1 &: \ p^{min} \leq p^h \leq p^{max} \\ C_2 &: \sum_{n \in N} \sum_{a \in EV_j} x^h_{j,a} \leq Energy^{max}_h, \quad \forall h \in H,\ i, j \in N \end{aligned} \tag{8}$$

3) Stackelberg Game Model: In this section, we modeled the interaction of EVs and SP_L using Stackelberg game theory as 1-leader, multi-followers. The SP_L, *i.e.*, leader's strategy is s_L and its space is S_L where as the strategy of EVs, *i.e.*, follower's is s_{F_j} and its space is S_{F_j}, where as $j \subseteq N$. The SP_L pay-off function is $J_L(s_L, s_{F_1}, s_{F_2}, \ldots, s_{F_j})$ and the utility function for EVs is $J_{F_j}(s_L, s_{F_j})$. Following steps describe the Stackelberg game model in P2P energy trading scheme.

1) For each strategy of SP_L is $s_L \in S_{L_N}$, EVs try to minimize the payment function to get the best response $R_{F_j}(s_L)$ as follows:

$$\min_{s_{F_j} \in S_{F_j}} J_{F_j}(s_L, s_{F_j}) = min \sum_{h=1}^{H} p^h \times \left(\sum_{a \in EV_j} x_{j,a}^h \right) \quad (9)$$

where, s_L, *i.e.*, the strategy of SP_L is given.

2) For SP_L, it tries to maximize its objective function based on the response from the EVs as follows:

$$\begin{aligned} &\max_{s_L \in S_L} J_L(s_L, R_{F_1}(s_L), \ldots, R_{F_j}(s_L)) \\ &= max \left\{ \sum_{h \in H} p^h \times \sum_{n \in N} \sum_{a \in EV_j} x_{j,a}^h \right. \\ &\quad \left. - \sum_{h \in H} Cost_h \left(\sum_{n \in N} \sum_{a \in EV_j} x_{j,a}^h \right) \right\} \end{aligned} \quad (10)$$

3) Let s_L^* be the optimal strategy solution for P2P energy trading problem and $s_{F_j}^* = R_{F_j}(s_L^*)$. $(s_L^*, s_{F_1}^*, s_{F_2}^*, \ldots, s_{F_j}^*)$.
It is called as Stackelberg game strategy (Equilibrium) and the structure of Stackelberg game model is as shown in Fig. 3.

IV. PETS: P2P Energy Trading Scheduling Scheme

The Stackelberg game has two sides: one is the follower side and the other is the leader side. SP_L represents the leader and EVs represent the followers on the blockchain network. Firstly, we find the best energy consumption using the followers' response function under the price given by SP_L. Secondly, we find the leader's strategy by maximizing the pay-off function based on the reaction function by EVs. If the rational solution exists on both sides then, we can find an optimal strategy for the Stackelberg game. But in the proposed system, the response function of the followers neither continuous nor differentiable. So, there is no systematic solution exists on the leader side. Hence, we propose Genetic algorithm instead of gradient-based algorithm to design a decision-making process to get the Stackelberg solution.

A. Optimal Real-Time Energy Consumption Scheduling for EVs

For all EVs, the payment minimization problem is defined in Eq. 5, which is a linear programming problem. We design a systematic solution for this payment minimization problem as follows:

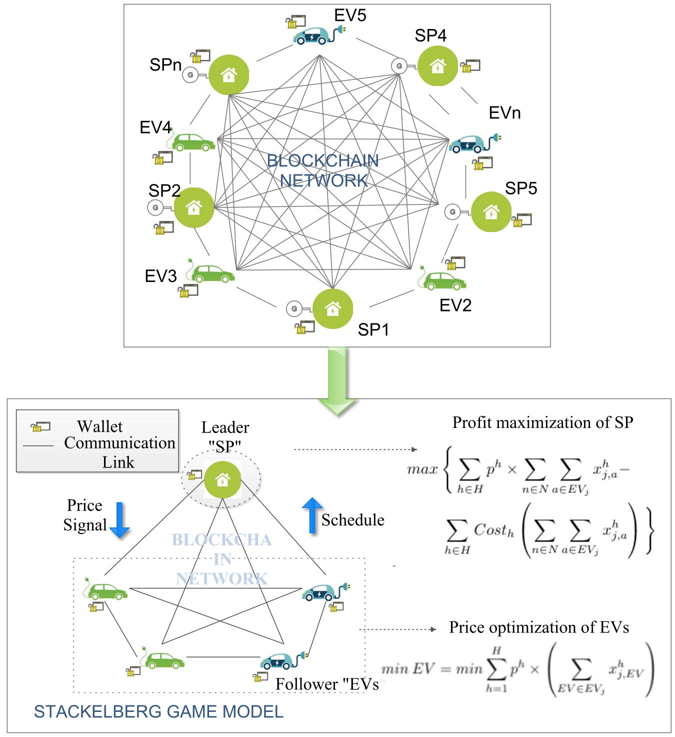

Fig. 3. The Stackelberg game model.

The payment minimization of problem Eq. 5 is redefined as follows:

$$min \sum_{EV \in EV_j} \left(\sum_{h=1}^{H} p^h \times x_{j,EV}^h \right) \quad (11)$$

For this linear programming problem, the optimization problem is calculated as follows:

$$\begin{aligned} &min \sum_{EV \in EV_j} f_{EV}(x_{EV}) \\ &s.t.\ C_1 : a \le g_{EV}(x_{EV}) \le b. \quad \forall EV \in EV_j \\ &\quad\ C_2 : h_{EV}(x_{EV}) = c, \quad \forall EV \in EV_j \end{aligned} \quad (12)$$

and the optimal solution for this optimization problem is same as Eq. 12 and is computed as:

$$\begin{aligned} &min f_{EV}(x_{EV}) \\ &s.t.\ C_1 : a \le g_{EV}(x_{EV}) \le b. \quad \forall EV \in EV_j \\ &\quad\ C_2 : h_{EV}(x_{EV}) = c, \quad \forall EV \in EV_j \end{aligned} \quad (13)$$

We decompose the payment minimization problem Eq. 11 of $|EV_j|$ into small problems, such that $|EV_j|$ is the number of EVs used in EV_j and is computed as follows:

$$\begin{aligned} &min \sum_{h=1}^{H} p^h \times x_{j,EV}^h \\ &s.t.\ C_1 : \sum_{h=\gamma_{j,EV}}^{\beta_{j,EV}} x_{j,EV}^h = E_{n_i,EV}, \quad \forall EV \in EV_j \\ &\quad C_2 : x_{j,EV}^h = 0, \quad \forall h \in H_{j,EV}, \ \forall EV \in EV_j \\ &\quad C_3 : \alpha_{j,EV}^{min} \le x_{j,EV}^h \le \alpha_{j,EV}^{max}, \quad \forall h \in H_{j,EV}, \\ &\quad \forall EV \in EV_j \end{aligned} \quad (14)$$

After that $H = (\gamma_{j,EV}, \ldots, \beta_{j,EV})$, $x^h_{n_i,EV} = 0$, $\forall h \in H_{j,EV}$, and $\forall EV \in EV_j$, we represent the Eq. 14 as follows:

$$\begin{aligned} &min \sum_{h=\gamma_{j,EV}}^{\beta_{j,EV}} p^h \times x^h_{j,EV} \\ &s.t.\ C_1 : \sum_{h=\gamma_{j,EV}}^{\beta_{j,EV}} x^h_{j,EV} = E_{j,EV}, \quad \forall EV \in EV_j \\ &\quad C_2 : \alpha^{min}_{j,EV} \le x^h_{j,EV} \le \alpha^{max}_{j,EV}, \quad \forall h \in H_{j,EV}, \\ &\quad \forall EV \in EV_j \end{aligned} \tag{15}$$

To solve the Eq. 15, the following steps are used.

- **Step I:** Assume $Price(\gamma_{j,EV} : \beta_{j,EV}) = (p^{\gamma_{j,EV}}, \ldots, p^{\beta_{j,EV}})$ denotes the energy prices scheduling for charging the EVs by SP_L and $M = \gamma_{j,EV}$ - $\beta_{j,EV}$ + 1 represents the number of hours in the scheduling time interval.
- **Step II:** Sort $Price(\gamma_{j,EV} : \beta_{j,EV})$ in an ascending order to get $Price'(\gamma_{j,EV} : \beta_{j,EV})$. When energy prices are low then, EVs consume more energy and vice-versa. So, it is important to find an optimal energy consumption scheduling for EVs under the $Price'(\gamma_{j,EV} : \beta_{j,EV})$, which is computed as follows:

$$\begin{aligned} &x'_{j,EV}(\gamma_{j,EV} : \beta_{j,EV}) \\ &\quad = \left[\alpha^{max}_{j,EV}, \ldots, \alpha^{max}_{j,EV}, x^*_{j,EV}, \alpha^{min}_{j,EV}, \ldots, \alpha^{min}_{j,EV}\right], \end{aligned}$$

whereas, $\alpha^{min}_{j,EV} \le x^*_{j,EV} \le \alpha^{max}_{j,EV}$,
If $\alpha^{max}_{j,EV}, \ldots, \alpha^{max}_{j,EV} = m$ then,
$\alpha^{min}_{j,EV}, \ldots, \alpha^{min}_{j,EV} = M - m - 1$
Substitute, $x'_{j,EV}(\gamma_{j,EV} : \beta_{j,EV})$ into C_1 of Eq. 15 to compute the following:

$$m.\alpha^{max}_{j,EV} + x*_{j,EV} + M - m - 1.\alpha^{min}_{j,EV} = E_{j,EV} \tag{16}$$

By using, $\alpha^{min}_{j,EV} \le x^*_{j,EV} \le \alpha^{max}_{j,EV}$, we have,

$$m = \frac{E_{j,EV} - M.\alpha^{min}_{j,EV}}{\alpha^{max}_{j,EV} - \alpha^{min}_{j,EV}} \tag{17}$$

whereas, [.] means capturing the nearest integer value.
Adding the value m to the Eq. 16, we get $x*_{j,EV}$.

To get $x_{j,EV}(\gamma_{j,EV} : \beta_{j,EV})$ by using $Price(\gamma_{j,EV} : \beta_{j,EV})$, we sort the $x'_{j,EV}(\gamma_{j,EV} : \beta_{j,EV})$ inversely on the basis of map between the $Price(\gamma_{j,EV} : \beta_{j,EV})$ and $Price'(\gamma_{j,EV} : \beta_{j,EV})$. From this, we get the optimal scheduling vector such as $x_{j,EV} = \left(x^1_{j,EV}, x^2_{j,EV}, \ldots, x^h_{j,EV}\right)$, whereas, $h \in H_{j,EV}$ and $x^h_{j,EV} = 0$.

Algorithm 2 presents the analytical solution for payment minimization problem.

B. Profit Maximization for the Leader SP

For SP_L profit maximization, we use search-based Genetic algorithm that includes selection, crossover, and mutation operations on a present population and create an optimal or near-optimal solution [59]. The profit maximization problem for SP_L is presented in Eq. 8, which is constrained optimization so we use penalty function [60] as follows:

$$\begin{aligned} &min\ f(\bar{x})\ \bar{x} \in Feasible \subset R^n \\ &s.t.\ C_1 : a_i(\bar{x}) = 0, \quad i = 1, 2, \ldots, m \\ &\quad C_2 : b_j(\bar{x}) \le 0 \quad j = m+1, \ldots, p \end{aligned} \tag{18}$$

There is a finite number of penalty functions used in Genetic algorithms but we use the fitness evaluation function, which provides an efficient solution as follows:

$$Evaluation(\bar{x}) = \begin{cases} f(\bar{x}) & if\ \bar{x} \in Feasible \\ K - \sum_{i=1}^{s} \frac{K}{m} & \text{otherwise} \end{cases} \tag{19}$$

whereas, m is the total constraints, s is non-violated constraints, and K is a constant with value 1×10^9 [60].

As defined in the Eq. 8, the profit maximization problem is solved by the Genetic algorithm. The five phases of the Genetic algorithm, *i.e.,* (i) population (ii) fitness evaluation, (iii)selection, (iv) crossover, and (v) bit flip mutation, which finds an optimal solution for profit maximization problem for SP_L. A brief description of each phase of the Genetic algorithm is described as follows:

1) **Population:** In this phase, we use a binary-coded representation of the population in the PETS scheme. As defined in Eq. 8, we set the parameters, *i.e.,* $8 \le p^h \le 14$ cents and length of binary digits after the decimal point is up to two places related to the values and precision of the variables, *i.e.,* 10^2. The length of the binary bits is represented as $length_b$ and is set as 10. Hence, we compute the $p^{max} - p^{min}$, which is defined as follows:

$$2^{length_b - 1} \le p^{max} - p^{min} \times 1/10^{-2} \le 2^{length_b} \tag{20}$$

Algorithm 2 Payment Minimization Problem

Input:
The energy prices for 24 hours: $Price = (p^1, p^2, \ldots, p^h)$.
The minimum and maximum energy: $\alpha^{min}_{j,EV}$ and $\alpha^{max}_{j,EV}$, respectively.
The daily energy consumption for EVs: $E_{j,EV}$.
The time interval EVs are scheduled: $H_{j,EV}$.
Output:
Optimal scheduling vector $x_{j,EV}$

procedure FUNCTION($Price, \alpha^{min}_{j,EV}, \alpha^{max}_{j,EV}, E_{j,EV}, H_{j,EV}$)
  As per $H_{j,EV}$, we get $Price(\gamma_{j,EV} : \beta_{j,EV})$,
  Sort $Price(\gamma_{j,EV} : \beta_{j,EV})$ to get $Price'(\gamma_{j,EV} : \beta_{j,EV})$,
  As per the Eqs. 16 and 17, we get $x*_{j,EV}$ and $x'_{j,EV}(\gamma_{j,EV} : \beta_{j,EV})$,
  Sort inversely $x'_{j,EV}(\gamma_{j,EV} : \beta_{j,EV})$ to get $x_{j,EV}(\gamma_{j,EV} : \beta_{j,EV})$,
  Using $h \in H_{j,EV}$, we have $x^h_{j,EV} = 0$ and then, we find $\left(x^1_{j,EV}, x^2_{j,EV}, \ldots, x^h_{j,EV}\right)$,
  return $x_{j,EV}$
end procedure

So, for the PETS scheme, the value is defined as follows:

$$\begin{aligned} 2^9 &\le (14-8)\times 10^2 \le 2^{10} \\ 2^9 &\le 600 \le 2^{10} \end{aligned} \tag{21}$$

In the PETS scheme, to handle the values and precision of the variables up to two decimal point, the binary representation of 10 bits is crucial. However, since the interval of [8.00 14.00] only requires a maximum of 600 numbers, employing the 10-bits representation unavoidably results in, for a significant portion of the samples.

2) **Fitness Evaluation:** In this phase, we evaluate the objective function defined in Eq. 6 for each chromosome produced in the population phase, which is defined as follows.

$$Cost_h(P_h) = m_h P_h^2 + q_h P_h + r_h \tag{22}$$

3) **Selection:** In this phase, we use tournament selection process for the binary representation based population defined in the PETS scheme. First, we choose two random individuals from the population and then, select the better one into the mating pool. The steps involved in the selection process is defined in the Algorithm 3. After the selection of the best individuals, we use elitism to make a copy of these individuals in the next generation. The steps involved for elitism in the selection process is described in the Algorithm 4.

Algorithm 3 Selection Process

Input: Population $(Pop_1, Pop_2, \ldots, Pop_N)$.
Size of tournament $t = 2$.
Output: $Pop'_1, Pop'_2, \ldots, Pop'_N$.

procedure FUNCTION(N)
  for $(i = 1; i \le N; i++)$ **do**
    $Pop'_i \leftarrow$ best individual chosen from $(Pop_1, Pop_2, \ldots, Pop_N)$ by picking *'t'* individuals randomly
  end for
  Return $(Pop'_1, Pop'_2, \ldots, Pop'_N)$
end procedure

4) **Crossover:** In this phase, we describe the crossover operation working in the PETS scheme. We set the crossover rate 'R_c' is 0.25. The description of the uniform crossover is described in the Algorithm 5.

5) **Mutation:** In this phase, we use bit-flip mutation for binary representation of genes in the PETS scheme. It is defined as one or more random bits are selected and flip them.

Algorithm 6 describes the payment bill minimization by maximizing the profit of the SP_L. It is the main algorithm of this paper where steps 2-6 show the interactions between a leader, *i.e.,* SP_L and the followers, *i.e.,* EVs. In step 3, the SP_L sets the 24-hour energy prices to the EVs having strategy $s_{L,i}$. In step 4, EVs react to the prices by minimizing the payment bill. Then, in step 5, based on the information of energy consumption scheduling, SP_L finds an optimal solution to maximize the profit using fitness evaluation. Lastly, after the finite number of iterations, an optimal profit price for SP_L and minimized payment bill having best response for EVs is obtained.

Algorithm 4 Elitism Process

1: **procedure** FUNCTION(P)
2:   Generate a random P population.
3:   Evaluate the P population and choose the C_{best} chromosome.
4:   Apply the operations, *i.e.,* selection, crossover, and mutation to get new P' population.
5:   Then, choose the C'_{best} and C'_{worst} chromosome represents the best and worst, respectively.
6:   **if** $C'_{best} \le C_{best}$ **then**
7:     $C'_{worst} = C_{best}$
8:   **else**
9:     No replacement
10:   **end if**
11:   Repeat from the step 2.
12: **end procedure**

Algorithm 5 Uniform Crossover

Input: $Parent_1$ and $Parent_2$ two given parents.
L represents the chromosome length.
R_c represents the crossover rate.
Output: $Parent'_1$ and $Parent'_2$ off springs.

procedure FUNCTION(L)
  for $(i = 1; i \le L; i++)$ **do**
    Choose a random number 'm' in the interval [0,1].
    if $m \le R_c$ **then**
      $Parent'_1(i) = Parent_2(i)$
      $Parent'_2(i) = Parent_1(i)$
    else
      $Parent'_1(i) = Parent_1(i)$
      $Parent'_2(i) = Parent_2(i)$
    end if
  end for
  Return ($Parent'_1$ and $Parent'_2$)
end procedure

C. Complexity Analysis

In this subsection, we discuss the time and space complexity of the proposed Algorithms 1, 2, 3, 5 and 6.

1) Time Complexity: In Algorithm 1, there is one "*for*" loop that contains N number of steps and takes *O(N)* time. All other operations take O(1) time. So, the total time computation of Algorithm 1 is *O(N) + O(1) = (O(N))*.

In Algorithm 2, all the operations and mathematical calculations take *O(1)* time. So, the total time computation of Algorithm 2 is *O(1)*.

In Algorithm 3, there is one "*for*" loop that contains N number of steps and takes *O(N)* time. All other operations take O(1) time. So, the total time computation of Algorithm 3 is *O(N) + O(1) = (O(N))*.

Algorithm 6 Profit Maximization Problem

Input: N: The number of chromosomes in a population.
s_{L_N}: The strategy of the SP_L denoted by each chromosome.
Output: Solve Profit maximization.

```
1: procedure FUNCTION(N)
2:     for (i = 1; i ≤ N; i++) do
3:         The SP_L plays a strategy s_L and set the prices of
           24-hour time by solving the i_th chromosome.
4:         The EVs EV_j react on SP_L's strategy, i.e., s_{L,i} by a
           best response s_{F_{j,i}} = R_{F_j}(s_{L,i}) and solve a payment min-
           imization problem to find an optimal energy consumption
           scheduling as in Eq. 5.
5:         By fitness evaluation based on s_{L,i} and s_{F_{j,i}}, we find
           to solve profit maximization problem as in Eq. 8.
6:     end for
7:     By using Selection, Crossover, and Mutation operations,
       created a population of new chromosomes.
8:     Goto steps 2 to 7 until the problem solves.
9: end procedure
```

In Algorithm 5, there is one "*for*" loop that contains L number of steps and takes *O(L)* time. All other operations take O(1) time. So, the total time computation of Algorithm 5 is *O(L) + O(1) = (O(L))*.

In Algorithm 6, there is only one "*for*" loop to evaluates the fitness function and find profit maximization that takes *O(N)* time. All other operations take O(1) time. So, the total time computation of Algorithm 6 is *O(N) + O(1) = (O(N))*.

2) Space Complexity: In Algorithm 1, the "*for*" loop takes *O(N)* space to compute the auction bid for SP_L. All other operations take O(1) space to compute. So, the total space complexity of Algorithm 1 is *O(N) + O(1) = (O(N))*.

In Algorithm 2, all the operations and mathematical calculations take *O(1)* space. So, the total space complexity of Algorithm 2 is *O(1)*.

In Algorithm 3, the "*for*" loop takes *O(N)* space to compute the new individuals. All other operations take O(1) space to compute. So, the total space complexity of Algorithm 3 is *O(N) + O(1) = (O(N))*.

In Algorithm 5, the "*for*" loop takes *O(L)* space to compute the off springs. All other operations take O(1) space to compute. So, the total space complexity of Algorithm 5 is *O(L) + O(1) = (O(L))*.

In Algorithm 6, the "*for*" takes *O(N)* space to find profit maximization by minimizing the payment bills by EVs. All other operations take O(1) space. So, the total space complexity of Algorithm 6 is *O(N) + O(1) = (O(N))*.

V. Performance Evaluation

In this section, we discuss the numerical settings and simulation results of the proposed PETS scheme.

A. Numerical Settings

In this section, we describe the simulation settings and parameters to evaluate the proposed PETS scheme. For simulation, we considered the EVs charging data having 113 customers for the period of January 2013 to June 2014 [61]. From this data set, we received half-hourly KWh measurements from the EV chargers. The scheduling period for the EVs are from 8 AM to 8 AM the next day.

TABLE II
Simulation Parameters

Parameters	Reference Value
q_h	0
r_h	0
m_h	5.5×10^{-4} and 4.0×10^{-4}
$E_{j,EV}$	9.9 KWh
$h \in H$ (24 hours)	8AM - 8AM
$\alpha_{j,EV}^{min}$	0.3 KWh
$\alpha_{j,EV}^{max}$	2.0 KWh
Chromosome length	10
Population size	200
Mutation probability	0.005
Crossover rate 'R_c'	0.25
p^{min}	8 cents
p^{max}	14 cents
$length_b$	10 bits
Terminate generation	500
Transaction rate	100, 200, 300, 400, 500, 600, 700
Message count	50
Batch time	0.5 sec

For the price of the energy given to the EVs by the SP, we proposed a scheduling scheme having a cost function of quadratic nature ($Cost_h(P_h) = m_h P_h^2 + q_h P_h + r_h$) is redefined as in Eq. 6. Let us assume the values, *i.e.,* $q_h = 0$ and $r_h = 0$ to evaluate the cost function for maximizing the profit for SPs by minimizing the payment bills by EVs. Also, we use $m_h = 5.5 \times 10^{-4}$ cents during the day (8 AM to 12 AM) and $m_h = 4.0 \times 10^{-4}$ cents at night time (12 AM to 8 AM the next day). In order to test the performance of the proposed PETS scheme, we have used the Python programming. The other parameters used for simulation are shown in Table II.

B. Results and Discussions

In this section, we evaluate the proposed PETS scheme in comparison to the existing state-of-the-art proposals using various performance evaluation parameters.

1) Impact on EVs Energy Load: In this section, we have observed that peak-to-average ratio (PAR) in the EVs load using the proposed PETS scheme. It is clear from the solution that the EV users are interested to reduce the payment bills while the SP wants to balance the energy load with a low PAR value.

Peak-to-average ratio (PAR): It is defined as the daily energy load for EVs as $EV_j = (EV_j^1, EV_j^2, \ldots, EV_j^h)$, whereas $h \in H = 24\,hours$. So, the total workload for all

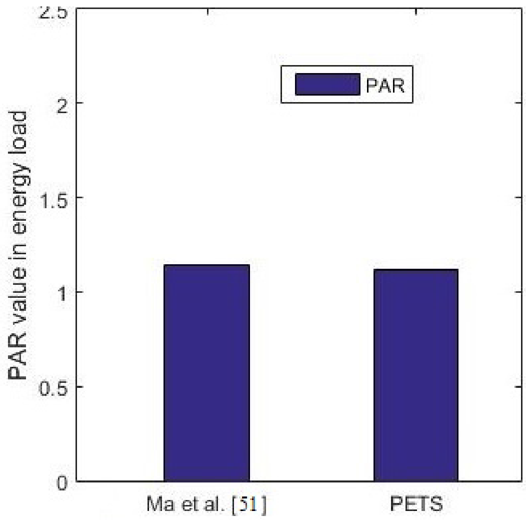

Fig. 4. PAR of the EVs load.

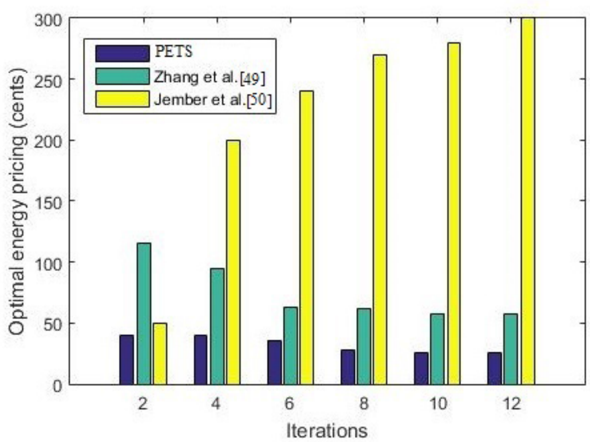

Fig. 5. Convergence of best response in PETS.

EVs at each hour is calculated as follows:

$$P_h = \sum_{j=N} EV_j^h \tag{23}$$

Then, the peak and average load of EVs are computed as follows [62]:

$$P_{Peak} = \max_{h \in H} P_h \tag{24}$$

$$P_{Avg} = \frac{1}{H}\Big(\sum_{h \in H} P_h\Big) \tag{25}$$

Hence, PAR is defined as follows:

$$PAR = \frac{P_{Peak}}{P_{Avg}} = \frac{H \times \max_{h \in H} P_h}{\sum_{h \in H} P_h} \tag{26}$$

From Fig. 4, we have observed that in the proposed PETS scheme, the average PAR in energy load of EVs reduces by 12.5% as compared to the existing scheme [51].

2) Impact on Energy Pricing: This section describes the impact of the proposed PETS scheme on the optimal energy pricing of SPs. Fig. 5 shows the concurrence of best response

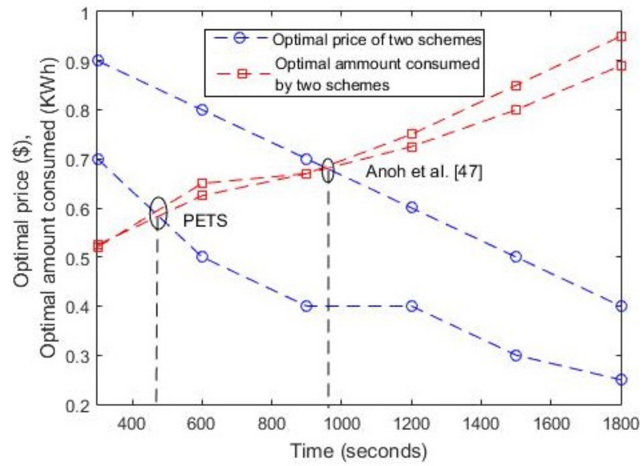

Fig. 6. Optimal pricing at different periods of PETS with the existing scheme.

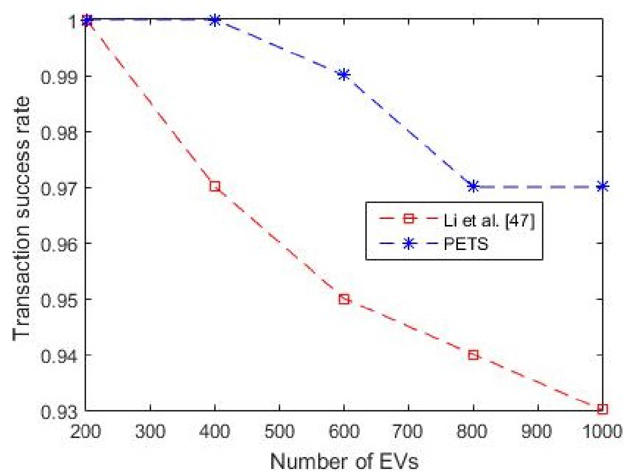

Fig. 7. Transaction matching rate of PETS with the existing scheme.

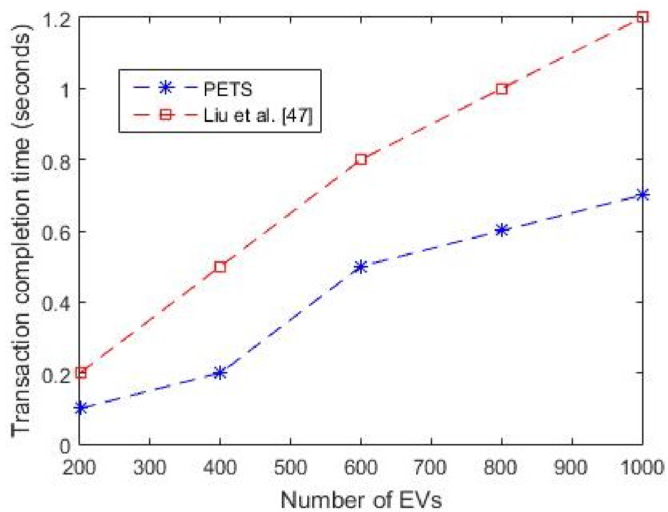

Fig. 8. Transaction efficiency curve of PETS with the existing scheme.

and the convergence of optimal energy pricing of SPs in the proposed PETS scheme. It clearly shows that the proposed scheme converges after *ten* iterations to one equilibrium

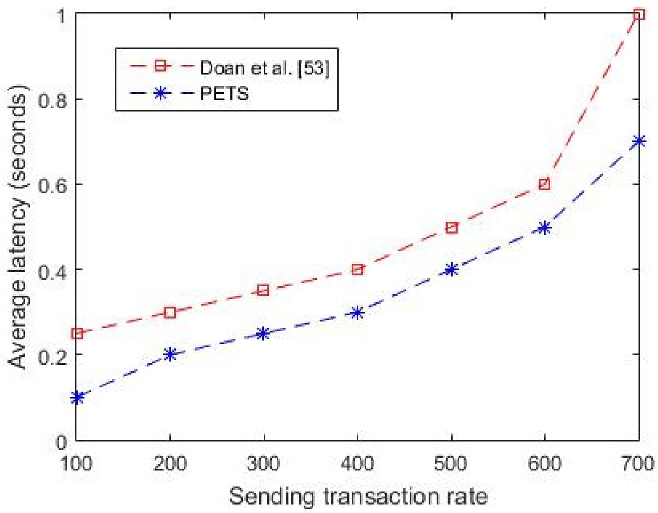

Fig. 9. Average latency of PETS with the existing scheme.

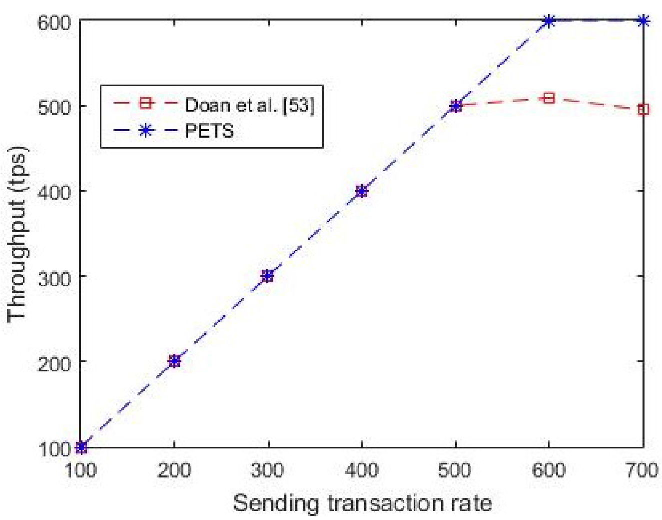

Fig. 10. Throughput of PETS with the existing scheme.

point compared to the existing schemes, *i.e.,* converges within 15 iterations [49] and after 15 iterations [50]. Fig. 6 shows the prices decrease as the trading period increases. EVs consume more energy at lower prices while SP sells more at a higher price. This figure shows the equilibrium point of price where both EVs and the SP found an acceptable price. In comparison to the existing scheme [52], the proposed PETS scheme have an unique equilibrium point with respect to time as shown in Fig. 6. Hence, the evaluation based on the proposed PETS scheme declares the capability and better convergence in optimal pricing for SPs compared to the existing schemes.

3) Impact on Transactions: This section describes the impact of the proposed PETS scheme on energy transactions. The comparison of two schemes for the transaction success rate is as shown in Fig. 7. It shows that the transaction rate is high when less number of EVs participate in P2P energy trading scheduling. Compared to the existing scheme [47], the proposed PETS scheme have a superior transaction success rate. Also, in Fig. 8, when less number of EVs

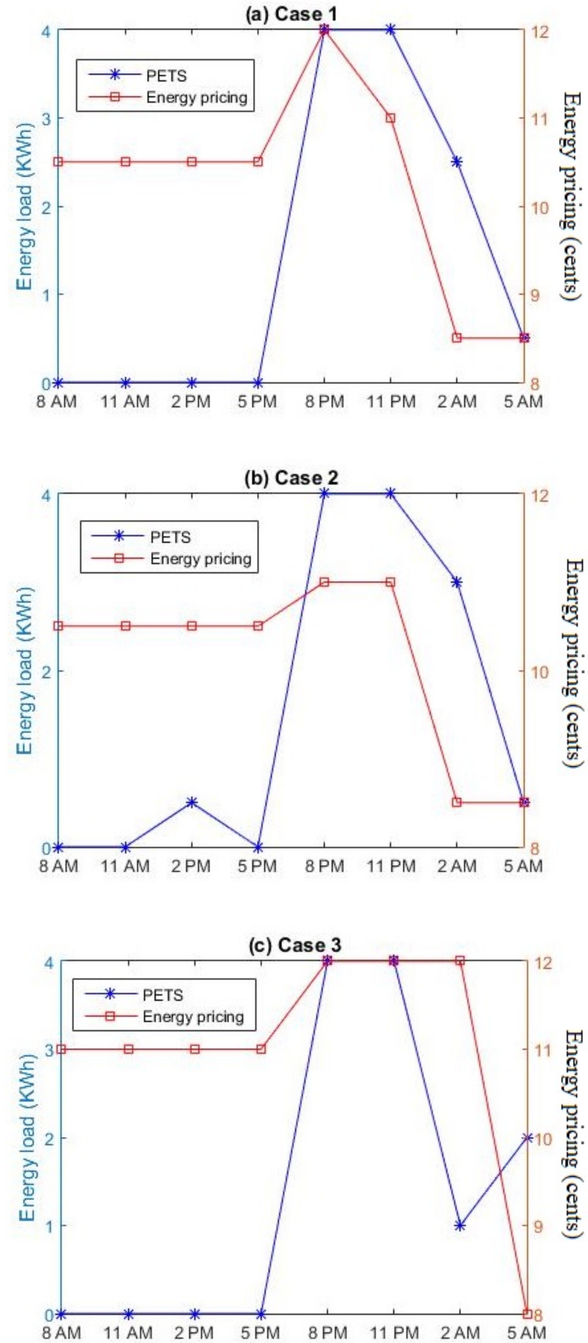

Fig. 11. Energy consumption for different EVs using PETS.

have participated in P2P energy trading, the time taken to complete the transaction is less in both the schemes. However, with an increase in EVs, the transaction completion time is also increasing. Compared to the existing scheme [47], the proposed PETS scheme takes less time to complete the transactions, which improves the transaction efficiency. From the results obtained, it can be inferred that the proposed PETS scheme supports fast and secure P2P energy trading.

4) Impact on Scalability: This section describes the impact of the proposed PETS scheme on the scalability of the system model. We simulated PETS at different transaction rates from 100 to 700 tps with a message count of 50 and batch processing time of 0.5 seconds. Compared to the existing

TABLE III
TIME-OF-USE TARIFF TIME BANDS

Tariff Bands	Times
Weekday (Peak)	16:00 - 20:00 (Mon-Fri)
Weekday (Day)	7:00 - 16:00 (Mon-Fri)
Weekday (Off-Peak)	Mon: 00:00 - 7:00 , Tue-Thur: 20:00 - 07:00, Fri: 20:00 - 00:00
Weekend	All-day

scheme [53], the proposed PETS scheme performs better in scalability metrics, i.e., average latency and throughput, are shown in Fig. 9 and Fig. 10, respectively.

5) Impact of Scheduling: In this section, we use ToU price for EVs where we partition the time, *i.e.,* 24 hours into three different bands such as peak, off-peak and day for every weekday [61]. The structure of ToU tariff bands is shown in Table III.

We have tested the genetic algorithm on three test cases, *i.e.,* Case 1: 24, Case 2: 90, and Case 3: 91 EVs are reported for evaluation. Fig. 11 clearly shows the daily payment of EVs. It shows that with the deployment of the proposed PETS scheme, the energy consumption of EVs is deviated from high prices to low in comparison to non-scheduling EVs.

VI. CONCLUSION

This paper proposes the PETS scheme based on energy consumption real-time pricing using blockchain technology in smart grid systems. We have considered EVs to minimize their energy payment bills and the SPs to maximize their profit. The interactions between EVs and the SP have been modelled using the Stackelberg game theory-based 1-leader, multi-followers, where SP_L is the leader and EVs are followers. Firstly, we select the leader among all SPs using a second-price reverse auction. Then, we used the Genetic algorithm to obtain the Stackelberg solution. Simulation results show that the proposed PETS scheme outperforms the existing scheme with respect to the various performance evaluation metrics. Currently, the PETS scheme focuses on one SP serving multiple EVs. In future work, a competitive energy market will be considered. Then, the Stackelberg game model will be modified into a multi-leader, multi-follower game. Moreover, we can consider a multi-stage Stackelberg game, where EVs and SPs are the players. Moreover, we will also explore the security and privacy issues with respect to the energy trading between EVs and the SPs.

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