Consensus Mechanism for Blockchain-Enabled Vehicle-to-Vehicle Energy Trading in the Internet of Electric Vehicles

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***Abstract*—Electric Vehicles (EVs) have emerged as one of the most promising solutions for reducing carbon emissions in smart cities. However, due to the limited battery life of EVs and the scarcity of charging stations, EV drivers are not willing to travel long distances. Thus, blockchain-enabled energy trading (BET) has lately been used to securely share energy among EVs via wireless power transfer (WPT) technology. Blockchain is used to ensure the security and privacy of transactions between untrustworthy EVs in the WPT process. Nevertheless, previous works on BET have relied on existing consensus mechanisms built on the requirements of the cryptocurrency systems. These consensus mechanisms have faced significant challenges in maintaining high reliability, throughput, low latency, and network scalability in V2V energy trading that requires real-time services. To address these issues, we propose a new consensus mechanism that leverages the benefits of Practical Byzantine Fault Tolerance (PBFT) and Proof of Reputation (PoR) called PBFT-based PoR (PPoR). The energy trading process runs in a clustered vehicular network, where validator selection, block generation, and consensus processes are performed in each cluster. We adopt an incentive mechanism based on a Stackelberg game model to optimize the utility of sellers, buyers, and validator nodes, which motivates honest and cooperative nodes. The simulation results show that the proposed scheme reduces buyers' costs by 21.1% while increasing the utility of sellers by 18%. Moreover, compared to benchmarks, the proposed scheme reduces the transaction processing delay and increases the throughput by more than 47.1% and 15.7%, respectively.**

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I. Introduction

The rapid development of intelligent transportation systems has been crucial in the realization of carbon-free and environmentally safe smart cities [1]. Over the last decade, governments, academia, and worldwide industries have given great attention to reducing urban pollution. Efforts have been made to advance the vehicular technologies to preserve global resources. As a result, electric vehicles (EVs), which use renewable energy sources such as wind, solar power, and biofuels were developed. EVs are a promising solution for combating climate change, reducing harmful exhaust emissions. They are becoming more common in recent years due to their low carbon emissions, modest cost, and environmental safety, which makes them more appealing to buy in general [1], [2]. Moreover, vehicle-to-vehicle (V2V) communication has gained much attention because of its significant potential to expand the use of intelligent transportation technologies including safety applications, on-board entertainment, and resource sharing [3]–[6]. In future intelligent transportation networks, EVs are anticipated to be one of the most critical modes of transportation and renewable energy users [7].

Energy demand has been rising rapidly as a result of the increasing number of EVs and smart devices embedded in their systems [8]. Besides, due to their limited battery life and higher energy requirements for appliances connected to them, EVs must be re-charged frequently for drivers to travel long distances to their destination [9]. On the other hand, cities have a scarcity of charging stations to meet the ever-increasing demand for EVs charging. Furthermore, the recharging of EVs is difficult when the vehicles are far from the charging station and have insufficient energy to reach the charging station. To address this issue, a vehicular energy network (VEN) has recently been used in the Internet of electric vehicles (IoEV) to facilitate V2V energy transportation across a broad geographical area by utilizing wireless power transfer (WPT) technologies [10]–[12]. The V2V energy sharing is a more convenient and flexible method of EVs charging, and it can help to reduce EV energy consumption [13]. The design and implementation of a V2V energy sharing network would dramatically reduce EV range anxiety while requiring minimal infrastructure investment. It

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also offers a valuable service to EV owners, local communities and municipalities, and the utility grid, particularly as a demand response tool during peak hours [14]. V2V energy sharing will allow EVs to dynamically re-charge their batteries from EVs with extra energy on their board at comparable transfer rates while both the seller and buyer are in motion [15].

However, the IoEV environment is supposed to be trustless, where energy sellers, buyers, and brokers are not honest enough [16]. The trading parties may have disputes concerning payments and sharing of energy. Also, due to the potential security vulnerability in IoEV, EV users can be attacked by external or internal adversaries [17]. Furthermore, due to the selfishness of EVs, it is a significant challenge to optimally charge/discharge EVs in order to achieve regional energy balance in IoEV. To address the aforementioned issues, authors in [1], [7], [18]–[20] introduced blockchain-enabled energy trading (BET) schemes to achieve secure energy delivery services between energy sellers and buyers. Blockchain is a digital ledger system that allows untrusted vehicles to keep distributed and transparent transaction records. It was initially designed for cryptocurrency exchange, but it is now being used in various industries, including health care, agriculture, education, resource sharing, and more, to ensure the security and privacy of transactions between untrusted nodes in a chain [21], [22]. The consensus mechanism is a core element of blockchain to maintain trust between untrusted nodes [23]–[25]. The efficiency of the blockchain systems considerably depends on the design of consensus mechanisms, and it strongly impacts the transaction processing rate, scalability, reliability, and security of the system [24], [26].

In the last decade, researchers have attempted to improve the efficiency of blockchain systems by developing a novel consensus mechanisms such as Proof-of-Work (PoW), Proof-of-Stake (PoS), Proof-of-Authority (PoA), Practical Byzantine fault-tolerant (PBFT), and Proof-of-Reputation (PoR). However, to the best of our knowledge, consensus mechanisms designed specifically to improve the efficiency of V2V energy trading in the IoEVs are still rare. Besides, previous studies on BET relied on these existing consensus mechanisms designed for cryptocurrency-based systems. Studies in [3], [26] witnessed that the current consensus mechanisms are not efficient for V2V energy trading because they require high computational resources to find validators, have a lot of communication complexity and cost during the consensus process. Currently, the EVs are embedded with intelligent devices to run real-time safety applications, on-road infotainment, and distribute resources in complex communication environments using their limited resources.

Therefore, we are motivated to design efficient consensus mechanisms for the BET deployed in the IoEVs to address the aforementioned problems of the V2V energy trading process. In this paper, we use a consortium blockchain to enable secure energy trading between energy requester (buyer) and energy provider (seller) vehicles. A Stackelberg game model is used to motivate energy buyer, seller, and consensus nodes as a utility maximization scheme. The main contributions of this work are presented as follows:

1) We design the PBFT-based PoR (PPoR) consensus model, in which the advantage of PBFT and PoR are integrated and harmonized to maintain secure, reliable, and distributed consensus in the BET system. We use a clustered vehicular network, in which EVs participating in the energy sharing system are grouped together based on their current location, speed, and direction. The validator selection, block generation, and block validation are performed in each cluster.
2) We adopt a logic-based trust management scheme for reputation calculation and validator selection in which validators are easily chosen based on their reputation rather than solving mathematical puzzles to be selected as a leader. The logic-based trust management scheme integrates subjective and objective trust.
3) To improve the utility and revenue of both the energy sellers and buyers, we use a two-stage Multi-leaders and Multi-followers (MLMF) Stackelberg game-based model. This model encourages energy sellers to share their excess energy with EVs that require energy to reach their destination. Furthermore, energy buyers can obtain energy with high quality of service (QoS) at a low cost.
4) We propose a pricing-based incentive mechanism based on a Stackelberg game model to motivate energy transaction validators involved in the BET. The proposed incentive mechanism rewards monetary value and allocates mining value to the validator EVs in order to encourage honest and cooperative nodes. Moreover, we perform extensive simulations to evaluate the performance of our proposed scheme in terms of utility optimization, throughput, latency, and scalability.

The rest of this paper is structured as follows: In Section II, we presented related works. The system model of V2V energy trading, including network model, cluster formation, blockchain-enabled V2V energy trading, and problem formulation are described under Section III. Section IV discusses the proposed consensus scheme, and Section V analyzes the performance evaluation and the simulation results. Lastly, we conclude the paper in Section VI.

II. Related Works

This section reviews recent research efforts focusing on energy sharing in the IoEV and consensus mechanisms commonly utilized in the BET system.

A. V2V Energy Transfer

Several studies have been conducted in order to present novel solutions for V2V and vehicle-to-grid (V2G) energy sharing. Authors in [17] presented bidirectional direct current to direct current (DC-DC) energy transfer. Alvaro *et al.* [20] proposed V2V energy transfer in a smart grid. Wang *et al.* [27] proposed a novel charging scheme for EVs in a smart community integrated with renewable energy sources based on a game theory approach. However, these energy transfer methods use an energy aggregator or transmit power between EVs in a conductive manner via a DC-DC converter, which reduces the

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energy transfer efficiency of EVs. Many WPT-based solutions have been proposed to address this issue. In [28], a direct V2V power transfer method via WPT was presented that does not require an energy aggregator. The authors in [29], [30] presented a review of the WPT technologies applied for EV charging. The studies in [10]–[12] have proposed V2V charging using WPT technologies. WPT has recently become very attractive for EV charging applications in both stationary and dynamic charging scenarios due to its advancements [12], [31], [32]. According to recent studies, WPT systems for EVs charging are classified into three types: stationary (SWPT), semi/quasi-dynamic (QDWPT), and dynamic (DWPT) [30]. The SWPT charging system which replaces the conductive charging system, allows EVs to share energy using an on-board receiving pad and an external charging pad in the pavement. The QDWPT systems can be deployed at bus and taxi stops and traffic lights to provide short-term charging in a dynamic environment. The DWPT systems allow EVs to charge their battery while they are in motion, increasing driving range and efficiency [10], [30]. As a result, the DWPT attracted more interest to use in EVs charging.

Moreover, blockchain technology has been employed in energy trading to guarantee the security and privacy of transactions kept by untrusted nodes. The authors in [33] presented an optimal bidding framework for V2G enabled local energy internet by taking carbon trading into account. Ashfaq *et al.* [18] proposed a blockchain-based k-nearest neighbor approach to energy trading for EVs with the goal of reducing resource consumption. Sun *et al.* [19] proposed a blockchain-enabled and fog computing-based V2V energy trading architecture to balance the interests of both charging and discharging EVs. Hong *et al.* [34] proposed a consortium blockchain-based V2G energy transaction system. The authors in [35] introduced a blockchain-assisted V2G energy trading framework. Danish *et al.* [36] presented a blockchain-enabled framework for EV charging services and trusted reservations. Lasla *et al.* [7] presented a blockchain-based energy trading architecture, which is a smart-contract-based trading platform that allows sellers to supply public charging stations and EVs to obtain energy at a reasonable price. Furthermore, the authors of [37] presented a novel permissioned energy blockchain system in VEN to implement secure wireless energy delivery services for EVs and energy nodes using distributed ledgers and cryptocurrency. The PoR consensus mechanism is used to assist EVs in reaching an agreement in energy trading transactions. The blockchain-enabled studies described above relied on legacy consensus structures, which are inefficient for providing the high throughput, reliability, low latency, and scalability that today's vehicular technology demands.

B. Consensus Mechanism

Several consensus algorithms have been created to enhance the efficiency of blockchains after the invention of blockchain (Bitcoin) in 2008. Satoshi Nakamoto's Bitcoin uses the PoW consensus algorithm, which is the most widely used crypto-currency-based consensus algorithm [38]. PoW is currently used in Bitcoin, Litecoin, Ethereum, and a variety of other private blockchains. In PoW, miners compete against one another by solving complex mathematical puzzles to be chosen as a leader. Solving these puzzles requires more computation resources and time. As a result, Ethereum proposed the PoS consensus protocol to address the issues of PoW. In PoS, the block miner is chosen at random based on the node's stake in the system [39]. Nevertheless, PoS is criticized for the centrality of consensus that occurs when wealthy stakeholders control the consensus process. As a solution to these issues, the Delegated PoS (DPoS) consensus protocol is proposed, in which each node selects a representative to create and approve blocks. DPoS processes transactions faster than PoS, but the consensus process is more centralized [40]. Similarly, Gavin Wood proposed PoA, in which validators stake their authority reputation rather than coins [41], and New Economy Movement (NEM) proposed Proof of Importance (PoI), which works similarly to PoS but adds more metrics to evaluate miner nodes [42]. Moreover, in [24] proposed PoR, in which validators are chosen based on their reputation, which is calculated using a subjective trust model. Furthermore, in 1999, Castro *et al.* [43] introduced the PBFT, which is now used in Hyperledger. To keep the network secure in PBFT, nodes involved in the consensus process must exchange messages with every other node, which increases communication complexity and cost as the network size grows.

Current research works related to the BET system have been utilizing the traditional consensus mechanisms designed based on the crypto-currency system requirements. For instance, the PBFT-based Delegated PoS (PDPoS) implemented for enhanced energy sharing in IoEV [19], PBFT for energy trading in V2G environment [22], and PoR used in [37]. The authors in [44] proposed an Enhanced Proof-of-Benefit (ePoB) consensus scheme to improve the protocol security and performance of the electricity exchange system in V2G. A reputation-based delegated BFT consensus algorithm is proposed in [45] to efficiently reach consensus in the permissioned energy blockchain. However, these existing consensus mechanisms are challenged to achieve efficient consensus in BET scheme. Considering the EVs' real problem and the service that the EVs are envisioned to provide in the building of smart cities, we design an efficient consensus mechanism called PPoR for the BET system deployed in IoEV to perform efficient V2V energy sharing. Our proposed scheme is different from others for various reasons. 1) In our scenario, the trading takes place in a clustered V2V environment, which shortens the distance between the energy seller and buyer allows both the seller and the buyer to consume as a minimum amount of energy as possible for communication and energy sharing. It also ensures that the entities in the blockchain share resources fairly and reasonably. 2) The reputation calculation model is designed based on both subjective and objective trust management schemes to increase fairness in the rating of EV reputation. 3) In PPoR, only the leader node can create a new block at a time to prevent the fork creation, and the consensus reached by only selected nodes reduces the communication complexity. 4) The game-based incentive mechanism designed to motivate the validator nodes significantly reduces consensus time and ensures

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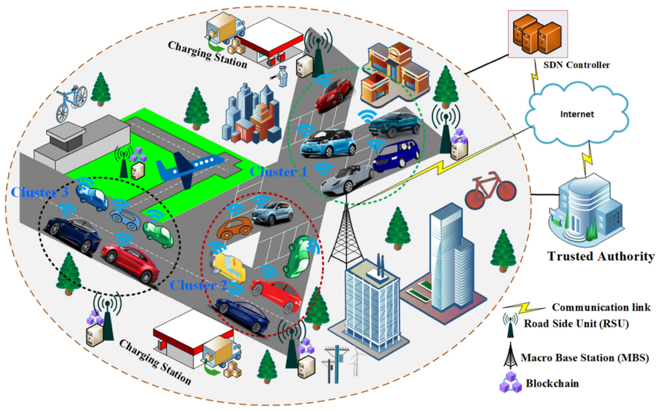

Fig. 1. System model for a clustered V2V energy trading.

block security. It can also improve the transaction throughput of the system.

III. System Model

In this section, we present a system model as shown in Fig. 1, where EVs are grouped into three clusters based on their current mobility information, direction/route, and speed. Each cluster consists of buyer, seller, and transaction validator. We utilize a consortium blockchain with a smart contract (SC) to ensure the security and privacy of the V2V energy trading system. The consortium blockchain is lightweight technology that has been used in various sectors, where only selected nodes participate in consensus process. It allows the energy requester EVs continually interacts with the system by requesting energy to charge their vehicle and then, they choose the best reasonable offer among the submitted bids. When required, the energy seller vehicle can purchase energy at lower prices directly from the electric grid, other EVs, and other energy sources such as solar, wind, biomass, and so on, and sell it to other vehicles at the best possible price. The SC is a slice of code deployed into the BET nodes/EVs and triggered by transactions stored in a BET network. The BET also keeps the new states of the SC whenever it is executed. In the EV charging scenario, the SC defines the energy trading logic, which runs whenever a new transaction to buy or sell energy is sent by buyers and sellers, respectively. The SC will behave logically based on its code and guarantee the implementation of terms and conditions that are agreed by parties. Overall, it can improve all participants' accountability, interoperability, and credibility in such a decentralized environment. Both buyer and seller EVs are equipped with a smart meter (SM) to report their consumed and produced energy, respectively. The SM is an essential element of the system, allowing for tracking the energy transfer between the buyer and seller concerning the corresponding pre-established energy purchase agreement.

A trusted authority (TA) is employed to issue the identity of entities involved in the energy trading system. The TA manages the network infrastructure, including the deployed SMs, and ensures their security and privacy. It also maintains the list of the registered users with their associated SCs, and the SC is used to enforce the entities to abide by the agreement they contracted. The charging stations are utilized as energy sources to provide power to nearby EVs, just like gasoline powers used for a fuel-based vehicle. Besides, to further improve the V2V communication network performance, road side units (RSUs) with wireless backhaul and macro base stations (MBSs) are deployed to provide wireless connectivity for the EVs. The Software Defined Networking (SDN) allows V2V network connectivity services to be programmable, allowing traffic flows to be dynamically directed and managed for maximum performance gains. The central SDN controller has a global and aggregated view of the V2V network.

A. Network Model

We assume that energy sellers, buyers, and transaction validators are clustered during the energy trading process based on their current mobility information. In VEN, we consider a number of clusters with EVs/users distributed randomly in their coverage areas and connected to RSUs. Let $j \in \mathcal{S}$={1,2,3,...,S} be the set of energy sellers, $i \in \mathcal{B}$={1,2,3,...,B} denotes the set of energy buyers, and $l \in \mathcal{N}$={1,2,3,...,N} denotes the set of validators in each cluster. Also, $\mathcal{S} \cup \mathcal{B} \cup \mathcal{N} = \mathcal{E} = \{1, 2, 3, \ldots., E\}$ represents the set of EVs in each cluster, and $z \in \mathcal{Z} = \{1, 2, \ldots, Z\}$ is the set of clusters. In the consortium blockchain network, each EV requires a unique identification address (ID) for identity authentication to be able to participate in energy trading legitimately. Hence, the buyers, sellers, and validators must register in the BET to get an account or public parameters and cryptographic keys that uniquely identify them in the energy trading system. To obtain the certificate, sellers must show that they have surplus energy to sell during the energy trading process, and buyers must also prove that they have transaction coins (ECoin) in their wallet to purchase the requested energy. First they get their certificates $Cert_{\mathcal{S}_j}$, $Cert_{\mathcal{B}_i}$, and $Cert_{\mathcal{N}_l}$ respectively from TA. The $\mathcal{B}_i$ can join the energy trading system using its certificate and obtain the public/private key pair ($PK_{\mathcal{B}_i}, SK_{\mathcal{B}_i}$), and wallet address ($Add_{\mathcal{B}_i}$). The account of $\mathcal{B}_i$ includes $Bal_{\mathcal{B}_i}$, certificate $Cert_{\mathcal{B}_i}$, current energy coin value e_i, public/private key pair ($PK_{\mathcal{B}_i}, SK_{\mathcal{B}_i}$), and wallet address $Add_{\mathcal{B}_i}$. Similarly, the seller's account contains its account balance $Bal_{\mathcal{S}_j}$, available energy, public/private key pair ($PK_{\mathcal{S}_j}, SK_{\mathcal{S}_j}$), and wallet address $add_{\mathcal{S}_j}$. To guarantee the authenticity and integrity of information exchange between sender and receiver, asymmetric encryption technology is applied in the blockchain [46], and it is expressed as:

$$D_{PK_x}(Sig_{SK_x}(H(m))) = H(m), \forall x \in \mathcal{E}, \tag{1}$$

where $Sig_{SK_x}()$ is the digital signature of sender x with its private key, $D_{PK_x}()$ is the decryption function with sender x's public key, and $H(m)$ is the hash digest of message m.

Moreover, TA is used as a parameter initializer to provide entity identity authorization and certificate issuance prior to running an energy blockchain. TA is in charge of generating public parameters and cryptographic keys and managing the identity of vehicles.

The energy provider and requester EVs are assumed to be in 2D space, and their locations coordinate can be expressed as (x_j, y_j), and $(x_i, y_i), \forall j \in \mathcal{S}, \forall i \in \mathcal{B}$, where (x_j, y_j) denotes

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location of j^{th} energy provider, and (x_i, y_i) represents location of i^{th} energy requester. The distance between the energy provider and requester is considered in the trading process [47]. The Euclidean distance between the EV j and EV i in each cluster is defined by:

$$d_{j,i} = \sqrt{(x_{j,z} - x_i)^2 + (y_{j,z} - y_i)^2}, j \in \mathcal{S}, i \in \mathcal{B}. \quad (2)$$

We consider the impact of cross channel interference (CCI) in the seller and buyer association problems. The Signal-to-Interference-plus-Noise Ratio (SINR) of i^{th} energy requester associated with the j^{th} energy provider is given as:

$$\ell_{j,i} = \frac{SPR(j,i)}{IE_{Agg}(j) + N_0}, \quad (3)$$

where $SPR(j,i)$ denotes the signal power received at the i^{th} energy requester from the j^{th} provider, $IE_{Agg}(j)$ is the aggregate interference encountered by the i^{th} requester, and N_0 refers the power spectral density of the Gaussian noise [48]. Furthermore, the transmission rate from energy provider j to requester i is expressed as: $\rho_{ji} = W \log_2(1 + \frac{\aleph g_{ji}}{\digamma \varpi^2})$, where W denotes the available bandwidth for each link, $\aleph$ denotes maximum transmission power at each EV, g_{ji} denotes the channel power gain from EV j to EV i for energy transfer, $\digamma$ represents the SINR gap from the additive white Gaussian noise channel capacity, and ϖ^2 denotes the noise power at the receiving side.

B. Power System Model

In our proposed V2V energy trading system, energy provider EV j obtains energy from the power grid or other EVs at a unit price of α_j^b and sells it to other EVs at a price of α_j^s. The energy provider constantly adjusts selling prices in the game to maximize its profit. The energy seller's pricing strategy must satisfy the following condition:

$$0 < \alpha_j^b(t) < \alpha_j^s(t), \forall j \in \mathcal{S}. \quad (4)$$

Let E^{min} be the minimum battery level threshold, and $E_i(t)$ be the battery level of EV i at time slot t. When $E_i(t) \leq E^{min}$, EV i sends an energy demand $\mu_{i,j}(t)$ and a maximum energy demand $\mu_{i,j}^{max}$ to the energy provider j that meets the following conditions [49].

$$0 \leq \mu_{i,j}(t) \leq \mu_{i,j}^{max} \leq C_{i,j}, \forall i \in \mathcal{B}, \quad (5)$$

where $C_{i,j}$ is the battery charging capacity of EV i. During EV charging, the initial state of charge $E_{i,j}^{ini}$, expected state of charge E^{exp}, and state of charge $E_{i,j}(t)$ at time slot t are used to calculate the amount of charged battery level. When the energy seller and buyer EVs start charging/discharging, the SM in the EV i records and reports the initial charge/battery level state. Each EV aims to be charged to its expected maximum energy level E^{exp} while minimizing its total energy purchase costs by making optimal demand price matching decisions; this should satisfy the following conditions [27]:

$$0 \leq E_{i,j}^{ini} \leq E_{i,j}(t) \leq E^{exp} \leq 1. \quad (6)$$

A linear model can be used to describe the battery dynamics of EV i [50] as:

$$E_{i,j}(t+1) = E_{i,j} + \frac{\Gamma_{i,j}\mu_{i,j}(t)\mathbb{I}_{i,j}(t)}{C_i, j}, \forall i \in \mathcal{B}, \quad (7)$$

where $\Gamma_{i,j} \in (0,1)$ is the battery charging efficiency of EV i. Besides, $\mathbb{I}_{i,j}$ denotes the indicator function used to present the EV state. It can be expressed as $\mathbb{I}_{i,j} = \{0,1\}$, where $\mathbb{I}_{i,j} = 1$ indicates that the EV is in a charging state and has not reached the expected charging level at time slot t, whereas $\mathbb{I}_{i,j} = 0$ indicates that the EV is in an ideal state and has reached the expected charging level at time slot t.

Electric storage unit: Let $E_j^{t-\Delta t}$, and E_j^t be the energy level of the electric storage units (ESU) of energy seller j at the beginning and end of the expected time slot. The charging and discharging power of seller j's ESU at a time slot t is assumed to be constant and is denoted by $C_{p,j}^t$ and $D_{p,j}^t$. We define binary variables $\vartheta_{c,j}^t$ and $\xi_{d,j}^t$ for seller j charging and discharging in time t, respectively, and $\vartheta_{c,j}^t$+$\xi_{d,j}^t \leq 1$. The energy stored in the ESU during charging and discharging is denoted by Ψ_j^t and $\hbar_j^t$, respectively, and is expressed as [9]:

$$\Psi_j^t = \vartheta_{c,j}^t C_{p,j}^t e_{c,j}^t \Delta t \quad (8)$$

$$\hbar_j^t = \frac{\xi_{d,j}^t D_{p,j}^t \Delta t}{e_{d,j}^t} \quad (9)$$

where $e_{c,j}^t$, and $e_{d,j}^t$ denote the charging and discharging efficiency of ESU for seller j, respectively, and Δt represents the length of each time slot. Therefore, the total energy stored in the ESU of EV j can be expressed as:

$$E_j^t = E_j^{t-\Delta t} + (\Psi_j^t - \hbar_j^t), \forall j \in \mathcal{S}. \quad (10)$$

The total available energy for seller j is denoted by $\chi = E_j^t - E_{min}^t$, where E_{min}^t is the minimum energy threshold that the seller j must maintain in its ESU. Besides, for EV j to sell its surplus energy to EV i, the following inequality must always be satisfied.

$$\mu_{i,j}^t \leq \chi, \quad (11)$$

where $\mu_{i,j}^t$ is the energy demand of the EV i at time t.

C. Cluster Formation and Cluster Head Selection

In this paper, we apply the K-Means clustering algorithm to build clusters based on current mobility information, direction, and speed of EVs, where each cluster has Cluster Head (CH) and assistant CH chosen by the Floyd-Warshall algorithm [51]. The CH and assistant CH act as an SDN controller to manage the EVs in the cluster, and in the event of a CH failure, the assistant CH takes over the controlling service to mitigate controller failure in the cluster [47]. As it is shown in Fig. 1, EVs in the BET system are classified into three different clusters. EVs interested in joining the clusters sends their current and previous mobility information to the nearby CH, and CH verifies the request and approves if it is legal. The mobility information consists of *vehicle-ID, cluster-ID, two-dimensional position*, and the *vehicle-role* in the energy trading process (buyer, seller

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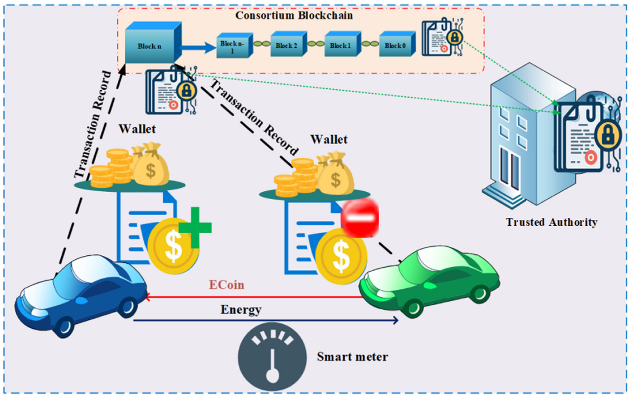

Fig. 2. Framework of blockchain-enabled V2V energy trading.

or validator). The mobility information of EVs could be directly integrated into the central SDN controller. The central SDN controller manages the incoming and outgoing traffic flows of clusters, while CH controls the flows within each cluster. The EVs can frequently change their cluster due to their high mobility and the dynamic nature of the route they pass through. Thus, to increase cluster stability, we choose clusters to be created based on the speed and vehicle's direction extracted from the GPS integrated within their system. The EVs moving on the straight line segment in the same direction will be clustered together. Moreover, the movement of an EV is defined by two random variables (S, T), where S is the EV speed, which has an equal probability of taking one of two possible state values (i.e., a lower speed L_s and a higher speed H_s). On the other hand, T represents the period that the EV moves at a constant speed before transitioning from L_s to H_s or vice versa. EV initially selects $L_s(H_s)$ and, after T, switches to the other speed $H_s(L_s)$ [52], [53]. We can adjust the time that an EV stays at a certain speed by changing the transition rate from L_s to H_s and vice versa and setting the L_s close to or equal to H_s. Therefore, this would help in determining optimal energy strategies for EVs while also maintaining cluster stability.

D. Blockchain-Enabled V2V Energy Trading

In this subsection, we describe the framework of BET shown in Fig. 2, which uses consortium blockchain with smart contracts as the core of the energy trading system in order to allocate energy from sellers to buyers optimally. The primary function of the BET is to maintain trust between all parties without relying on a trusted third party. This consortium blockchain-based energy trading integrates the sellers, buyers, TA, and validators to perform secure, distributed, and efficient block validation and verification. The vehicles that need to purchase energy continually interact with the BET system, and validators facilitate the energy trading between buyers and sellers.

In the BET, only authorized EVs can participate in the consensus and verify the validity of a block. The detailed energy trading process is summarized as follows:

1) System initialization: The TA initializes the trading system by issuing unique identifiers to entities involved in the energy trading process. After passing identity authentication by the TA, each participant in the BET system becomes an authorized entity with unique registration information. During system initialization, an elliptic curve digital signature algorithm [54] and asymmetric cryptography [45] are used to ensure data integrity and transaction unforgeability in the BET.

2) Reputation-based validator selection: We apply a reputation-based validator selection method, in which the validator's reputation is calculated using both subjective and objective trust logic models. The subjective trust logic evaluates the previous transaction validation, verification, and audit records of the nodes involved in the consensus process by collecting opinions about each node from all participants. The EV that is interested in becoming a validator candidate must provide the TA with identity-related information and obtain the certificate $Cert_{\mathcal{N}_l}$ before participating in verification. The TA then verifies the legality of the consensus nodes/validators by evaluating the information they provided and issues the certificates to validator EVs who passed the authentication.

3) Energy trading between buyers and sellers: Initially, $\mathcal{B}_i$ sends an energy request to the cluster head (CH) and the CH collects, arranges and stores it in the transaction pool. The leader node computes total energy demands and broadcasts them to the energy providers. The energy supplier EVs then determine their initial energy to be sold and the corresponding price using a pricing scheme designed on the basis of a game theory model to motivate sellers and buyers. Energy sellers in the blockchain adjust their pricing strategies non-cooperatively to maximize their profit, and buyers base their decisions on the prices offered and QoS estimated by the sellers, and provide responses to the leader. The buyers also consider the distance, speed, and direction of the energy provider to make an energy purchase decision. Vehicles moving in the same direction, speed and close distance will utilize small amount of energy to perform V2V charging. The leader then coordinates and orchestrates energy supply and demand between sellers and buyers. Finally, once the energy trading agreement is reached, $\mathcal{B}_i$ transfers energy coins from its wallet to the wallet address provided by the $\mathcal{S}_j$ based on smart meter readings.

E. Problem Formulation

In the energy trading system, the buyers purchases energy from sellers in order to travel long distances to their destination. However, vehicles with surplus energy may not be willing to share their energy with other vehicles that have low energy without some compensation. Therefore, to motivate sellers to share their excess energy with purchasers, an incentive technique must be used that allows both buyers and sellers to maximize their utility. Since both sellers and buyers are rational and selfish in the process of energy trading, they all seek to maximize their own benefits. Therefore, a game-theoretic strategy is used to tune energy demand and supply in our energy blockchain and achieve optimal energy trading agreements between the sellers and buyers. We employ a two-stage MLMF Stackelberg game model to optimize seller and buyer profits.

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Let define α_i as the price for each unit of energy provided to the $\mathcal{B}_i$ and η_i represents the energy that $\mathcal{B}_i$ intends to purchase. The seller also incurs other overhead cost ψ while performing the trading such as maintenance, electricity, hardware loss and operation costs. The utility function of the sellers is expressed as:

$$U_{\mathcal{S}_j}(\alpha, \eta) = \sum_{i \in \mathcal{B}}^{B} \alpha_i \eta_i - \sum_{i \in \mathcal{B}}^{B} \psi_i \eta_i, \tag{12}$$

where α is the energy price vector with $\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_B]^T$, and η is a vector of energy purchased by buyers with $\eta = [\eta_1, \eta_2, \ldots, \eta_B]^T$. Note that $\forall_i$, η_i is a function of α_i, i.e., $\eta_i \triangleq f(\alpha_i)$, which indicates that the energy that each buyer willing to buy depends on its allocated energy price. Also, it is assumed that the total available surplus energy of the $\mathcal{S}_j$ is χ, i.e., the total allocated energy for all the buyers should not be larger than χ.

Furthermore, each buyer should also consider its real demands while purchasing energy to determine the cost of buying energy. The utility function of buyers is expressed as:

$$U_{\mathcal{B}_i}(\eta_i, \alpha_i) = \omega_i \log_2 \left(1 + \frac{\eta_i}{\mu_i}\right) - \eta_i \alpha_i, \tag{13}$$

where $\log_2(1 + \frac{\eta_i}{\mu_i})$ is energy obtainment gains, ω_i is a positive coefficient that is used to convert the energy obtainment revenues into monetary reward, and $\eta_i \alpha_i$ is the cost incurred by buyer to obtain η_i energy. The energy obtainment gain is an increasing function of purchased energy η_i. The log function can also reveal the degree of satisfaction of buyers when receives η_i energy for the demand μ_i.

F. MLMF Stackelberg Game Formulation and Analysis

In this paper, we formulate a mathematical model as a two-stage MLMF Stackelberg game where sellers act as leaders and buyers act as followers. Both the sellers and buyers constantly adjust their strategies to maximize their reward. The leaders first announce the initial price of the energy to be sold, and the followers then request the energy based on the leaders' unit price. As a result, sellers compete with one another to sell their excess energy by setting their individual prices and estimate QoS levels in a non-cooperative manner as shown in Fig. 3. The buyers then consider the prices and estimated QoS of sellers to make a matching decision. In addition to the price given by the energy supplier j, the Euclidian distance $d_{j,i}$ and SINR $\ell_{j,i}$ between them are taken into account by the energy requester EV i when making a matching decision. Under the pricing-based incentive mechanism, the seller's objective is to increase its revenue from selling the energy to the buyers, whereas the buyer aims to enhance its obtainment by minimizing energy purchasing costs. Therefore, each leader must determine an optimal price α in order to maximize utility (revenue) within the constraints of their available resources. Similarly, each follower decides to optimize its utility by minimizing costs while maintaining the desired QoS. In this way, the sellers gain a certain amount of profit from the buyers, and each buyer can purchase some surplus energy from the seller and extend their battery to travel a long distance.

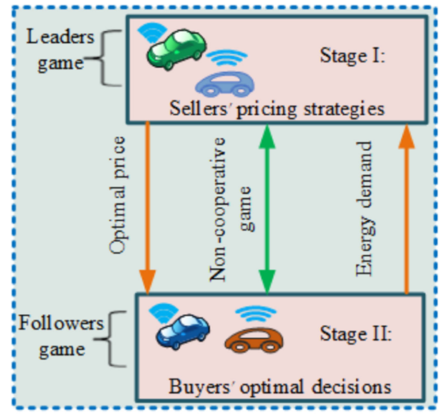

Fig. 3. Two stage MLMF Stackelberg game.

This game aims to find the Stackelberg equilibrium (SE) point(s) where both the leaders and the followers benefit the most. Let $d_{j,i}^{max}$ be the maximum Euclidian distance threshold, and $\ell_{j,i}^{min}$ be the minimum SINR threshold between energy supplier EV j and buyer EV i. The optimization problems of the energy trading are presented as below:

Stage 1: Leaders' Energy Pricing:

$$\begin{aligned} &\max_{\alpha \geq 0} U_{\mathcal{S}_j}(\alpha_i, \eta_i) \\ &\textbf{s.t.} \quad \sum_{i=1}^{B} \eta_i \leq \chi, \mu_{i,j}^t \leq \chi \end{aligned} \tag{14}$$

Stage 2: Followers' Energy Purchasing:

$$\begin{aligned} &\max_{\eta \geq 0} U_{\mathcal{B}_i}(\eta_i, \alpha_i) \\ &\textbf{s.t.} \quad U_{\mathcal{B}_i} > 0, \\ &d_{j,i} \leq d_{j,i}^{max}, \\ &\ell_{j,i} \geq \ell_{j,i}^{min}. \end{aligned} \tag{15}$$

$$U_{\mathcal{S}_j}(\alpha^*, \eta^*) \geq U_{\mathcal{S}_j}(\alpha, \eta^*), \tag{16}$$

$$U_{\mathcal{B}_i}(\alpha^*, \eta^*) \geq U_{\mathcal{B}_i}(\alpha^*, \eta). \tag{17}$$

Moreover, to show the existence of SE in our game, we present the second-order derivative of the utility functions of the seller and buyer in Equations (12) and (13), respectively.

$$\frac{\partial^2 U_{\mathcal{S}_j}}{\partial \alpha^2} = -\frac{2\psi}{\alpha^2} \frac{(N-1)}{N} \leq 0, \tag{18}$$

$$\frac{\partial^2 U_{\mathcal{B}_i}}{\partial \eta^2} = -\frac{\omega_i}{\ln 2(\mu_i + \eta_i)^2} \leq 0. \tag{19}$$

The SE of the proposed MLMF Stackelberg game can be defined as follows:

Definition 1: Let α^* and η^* are the optimal price of energy supplier and energy demand of buyer, respectively, and the point (α^*, η^*) is the SE if it satisfies the following conditions.

Equations (18) and (19) show that $U_{\mathcal{S}_j}$ and $U_{\mathcal{B}_i}$ are strictly concave. Hence, the SE exists in the formulated Stackelberg game. In this scenario, to achieve SE, $\mathcal{S}_j$ sets its decisions of energy price α_i for every energy requester $\mathcal{B}_i$ separately. After

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Algorithm 1: MLMF Stackelberg Game-based Optimal Energy Trading.

Input: Bid price $\theta_i = (\eta_i, \alpha_i)$ for all EVs where $\eta_i=$ requested energy and $\forall i \in \{1, 2, ..., B\}$;
Output: optimal utility for seller and buyer;
Assume δ is small positive constant, $\Delta\gamma$ is the small step size and ε is the allocated energy;
for $i = 1 : B$: **do**
  if $\sum_{i \in B} \mu_i > \chi + \delta$ **then**
    The seller increases price by $\Delta\gamma$
  else if $\sum_{i \in B} \mu_i < \chi - \delta$ **then**
    The seller decreases price by $\Delta\gamma$
  else
    if $\varepsilon_i < \mu_i$ **then**
      Compute allocated energy ε_i as:
        $\varepsilon_i = min(\mu_i, \frac{\alpha_i}{\gamma}\chi)$;
      Compute the cost C_i as:
        $C_i(\varepsilon_i(\theta), \alpha_i) = \varepsilon_i \alpha_i$;
      Compute Utility of seller as:
        Equation (12);
      Compute Utility of buyer as:
        Equation (13);
    end if
  end if
end for
SE is achieved;

collecting bids θ from S sellers, the total price γ offered by all sellers is calculated as follows:

$$\gamma = \sum_{i=1}^{S} \alpha_i. \tag{20}$$

Then, the buyers observe the sellers' decision and react with the best outcome of energy η_i as shown in **Algorithm 1**.

IV. Proposed PPoR Consensus Scheme

This section discusses the overview of the proposed consensus scheme, validator selection, reputation calculation, block generation, consensus process, and incentive scheme.

A. Overview of PPoR

The main goal of the PPoR consensus scheme is to achieve secure, distributed, reliable, and efficient consensus in BET; and maintain equality and fairness among consensus nodes to participate in block validation and get rewarded. We investigate the BET system's real problem and design an efficient PPoR consensus mechanism to improve energy sharing between two EVs (sellers and buyers).

Every energy request is processed within the cluster, which includes energy sellers, buyers, and validators as members. Validators are selected in the cluster based on their reputation value, and they are responsible for reaching a consensus on a newly generated block in their respective cluster. We adopt reputation calculation model based on subjective and objective trust schemes. The evidence and opinion spaces are collected from EVs in each cluster and recorded in the system to calculate the reputation value of each node. In our proposed model, EVs' reputation value is calculated and stored in the chain automatically after the new block is recorded to the BET. The entire nodes in the blockchain know the validators of the next block. Besides, to prevent possible attacks such as double spending, Sybil attacks, and 51% attacks, we adopt the advantages of the PBFT consensus mechanism. Hence in this scheme, the block is officially recorded to the chain only when 80% or more validator nodes verify its legitimacy, which means it tolerates 20% faulty nodes.

B. Reputation-Based Validator Selection

This subsection explores how block-validators are chosen to add new blocks to the BET system. In the consortium blockchain, only selected nodes are responsible for making a consensus in adding and verifying transactions in the blockchain. Since the energy trading occurs within the cluster, only three-fourths of the highly reputable EVs in the cluster are chosen as validators based on their reputation value. In the process of block mining, only one node (leader) is accountable for making a new block and broadcast to other validators, and then validator nodes verify the new block broadcasted by the leader. In PPoR, no puzzle solving competition is required to be a leader; instead, it can be chosen based on EVs' reputation value. A node with the highest reputation value is taken as a leader. Our proposed scheme calculates the reputation value of EVs to determine their status and incentive. The EVs with higher reputation value can be validators and incentivized based on their contribution to mining work.

C. Reputation Calculation

The reputation can be calculated by jointly considering a subjective and objective trust of EVs involved in the energy trading process. The trust in a V2V network presents the characteristics of both objective and subjective aspects [55].

1) Subjective trust scheme: Can be calculated by considering honesty, efficiency, and service score. We assume that honesty can be gained by comparing the inconsistency to the objective opinions from other participants. To obtain efficiency, we consider the number of audited transaction, audit result forward and response time compared with the minimum threshold time T_t. Total efficiency time $E_{all} = T_{audit} + T_{forward} + T_{response}$ and the efficiency $E_{i,j}$ is defined as:

$$E_{i,j} = \min\left(\frac{T_t}{E_{all}}, 1\right). \tag{21}$$

Finally, we consider the participation and success rate of consensus nodes as the service score.

2) Objective trust scheme: In V2V energy trading, subjective trust opinion may be biased or untrustworthy. Therefore, the objective trust is used together with the subjective trust scheme. The objective trust can be regarded as a weighted sum of various trust opinions, and a list of factors that determine the weights. At this point, to reflect the features of V2V networks,

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we mainly consider participation, maturity, success rate and earned mining value. Let $\pi \in [0, 1]$ is number of tasks validator participated, $\nu \in [0, 1]$ represents the earned mining value, and $\zeta \in [0, 1]$ denotes the successful validation made by the consensus node. Thus, the participation and success rate of validators expressed as:

$$\pi_l = \frac{\pi_l}{t}, \qquad \zeta_l = \frac{\zeta_l}{\pi_l}, \tag{22}$$

where t is the total block validation task. Besides, the earned mining value of validators can be calculated as:

$$\nu_l = \frac{\nu_l}{\sum_{i=1}^{N} \nu_l}. \tag{23}$$

To obtain a precise reputation value, a three-weight subjective logic enabled reputation management scheme is used. In this reputation management scheme, the evidence space and opinion space between buyer i and seller j can be described as $\{\Phi_{i,j}, \beta_{i,j}, \varphi_{i,j}\}$ and $w_{i,j} := \{b_{i,j}, d_{i,j}, u_{i,j}\}$, respectively. The opinion space can be mapped to the evidence space as shown in Equation (24), where $\Phi_{i,j}$, $\beta_{i,j}$ and $\varphi_{i,j}$ denote the numbers of positive behaviors, negative behaviors, and uncertain behaviors, correspondingly. Similarly $b_{i,j}, d_{i,j}$, and $u_{i,j}$ show the probabilities of "belief," "distrust," and "uncertainty," respectively. Let $b_{i,j}, d_{i,j}, u_{i,j} \in [0, 1]$ and $b_{i,j} + d_{i,j} + u_{i,j} = 1$. Then, we can calculate the possible reputation value based on subjective opinion as in Equation (24) and (25).

$$\begin{cases} b_{i,j} = \frac{\Phi_{i,j}}{\Phi_{i,j}+\beta_{i,j}+\varphi_{i,j}}, \\ d_{i,j} = \frac{\beta_{i,j}}{\Phi_{i,j}+\beta_{i,j}+\varphi_{i,j}}, \\ u_{i,j} = \frac{\varphi_{i,j}}{\Phi_{i,j}+\beta_{i,j}+\varphi_{i,j}} \end{cases} \tag{24}$$

$$\rho_l^{sub} = b_{i,j} + \epsilon u_{i,j}. \tag{25}$$

Then, we can define the subjective opinion space as $w_{i,j}^{sb} = \{b_{i,j}^{sb}, d_{i,j}^{sb}, u_{i,j}^{sb}\}$ and the objective one as $w_{i,j}^{ob} = \{b_{i,j}^{ob}, d_{i,j}^{ob}, u_{i,j}^{ob}\}$.

Furthermore, the total opinion space $w_{i,j}^{total} = \{b_{i,j}^{total}, d_{i,j}^{total}, u_{i,j}^{total}\}$ can be expressed as:

$$\begin{cases} b_{i,j}^{total} = \frac{b_{i,j}^{sb} u_{i,j}^{ob} + b_{i,j}^{ob} u_{i,j}^{sb}}{u_{i,j}^{sb} + u_{i,j}^{ob} - u_{i,j}^{sb} u_{i,j}^{ob}}, \\ d_{i,j}^{total} = \frac{d_{i,j}^{sb} u_{i,j}^{ob} + d_{i,j}^{ob} u_{i,j}^{sb}}{u_{i,j}^{sb} + u_{i,j}^{ob} - u_{i,j}^{sb} u_{i,j}^{ob}}, \\ u_{i,j}^{total} = \frac{u_{i,j}^{sb} + u_{i,j}^{ob}}{u_{i,j}^{sb} + u_{i,j}^{ob} - u_{i,j}^{sb} u_{i,j}^{ob}}. \end{cases} \tag{26}$$

$$\rho_l^{total} = b_{i,j}^{total} + \epsilon u_{i,j}^{total}. \tag{27}$$

Finally, we calculate the reputation value ρ_l^{total} based on both subjective and objective opinion spaces as in Equation (27), in which ϵ is a predefined constant reflecting the degree of influence of uncertain behaviors on the trust value.

D. Block Generation Process

We create a block data structure to meet the needs of energy trading in a clustered trading environment. The cluster information (CI) field has been added to the block data structure to improve transaction execution time, overall block production time, and system scalability. As shown in Fig. 4, a block data consists of two sections: the block header and the transaction section, with the block header section containing the block height, version, CI, timestamp, previous block hash, and signature, and the transaction section containing the transaction Merkle root. The block generation process begins with the creation of transactions, in which buyers send energy purchase requests to the blockchain. When an energy transaction request is sent to the BET, the CH node collects and stores it in the transaction pool. The leader then begins to coordinate the process of reaching a consensus.

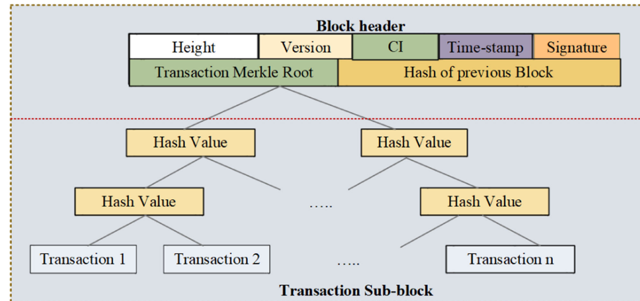

Fig. 4. PPoR block data structure.

E. PPoR Consensus Process

In a blockchain, all records are publicly verifiable and available to each node in the network. After successful transaction validation via a consensus mechanism, a block is added to the chain in chronological order. A linked list structure of a block makes each block references its parent through its unique cryptographic hash links to ensure the security and immutability of energy transaction records. The hash is formed through the SHA256 cryptographic algorithm, which helps to identify each block. The consensus mechanism ensures all participating nodes' mutual agreement for transaction validation, updating, and synchronization in a digital ledger. In the BET, EVs need to agree on a set of energy transactions to add in a block using an efficient consensus algorithm. In this scheme, block validation can be performed by a group of consensus nodes located in the same cluster. The aim of grouping nodes into different clusters is to allow nodes to reach consensus in a faster and more reliable manner, where nodes in the local group exchange votes and reach consensus locally. The leader will then upload the local consensus to the global chain. To synchronize the block in the global chain, leaders of each cluster involves in block validation. As illustrated in Fig. 5, each round, the cluster leader collects transactions based on the current location and path of the energy requesting EV, packs them into blocks, timestamps, and broadcasts to other authorized consensus nodes in the cluster with its signature for validation and verification.

These consensus nodes check the validity of the block data received from the cluster leader and broadcast their audit outcomes to other validators with their signatures for joint supervision and assurance. After receiving the audit results, each consensus node compares its work with others. If the transaction is legal and the

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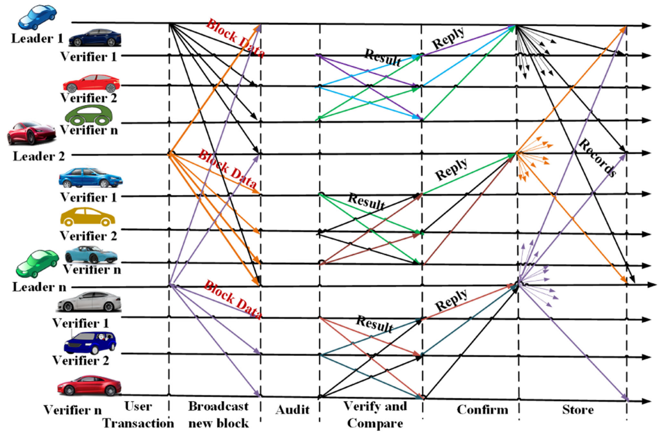

Fig. 5. PPoR consensus process.

signature is correct, they will vote on the transaction block and sends a reply to the cluster leader. This reply consists of the node's audit result, comparison result, signatures, and records of received audit results. The leader analyzes the received responses from consensus nodes.

Suppose the leader node receives a valid vote from three-fourth or above of the consensus nodes. In that case, it will append the block to the global chain and sends updates, including current audited block data and a corresponding signature to all authorized validator nodes for storage in their local chain. The detailed consensus process of PPoR is shown in **Algorithm 2**.

After the block is stored in the consortium blockchain, energy coins are awarded to the consensus nodes based on their contribution to the block mining and increment each node's mining value who successfully validated the block.

F. Incentive Mechanism

In this paper, we adopt a game theory-based pricing incentive scheme to motivate honest and cooperative vehicles involved in block validation process. The game theory strategy is an applied mathematical theory that models and analyses the systems where each node attempts to find the best strategy selected by others to reach consensus [56]. The proposed scheme rewards monetary incentives and mining value for cooperating nodes and punishes misbehaving malicious nodes. The SC integrated with the blockchain ensures that the service level agreement signed by task owners (TOs) and validators is obeyed. The two-stage Stackelberg game is formulated as MLMF, where TOs act as leaders and block validators act as followers to maximize their reward by actively participating in block mining activities. The TOs in this game are both EPs and ERs who pay a mining incentive for the transaction they initiated. The set of TOs is denoted by $f \in \mathcal{F} = \{1, 2, \ldots, F\}$, and each TO f strategizes its pricing to maximize its utility.

In the first stage, for $N \geq 2$ nodes qualified for participating in consensus, TO f announce reward/price for unit of mining task $\sigma > 0$ and the total available task Υ, motivating nodes to participate in the mining work.

Algorithm 2: PPoR-Based Consensus Process.

Input: List of authorized validators; Transaction block;
for Round i **do**
  Get N validators sorted based on reputation value;
  A validator with highest reputation value(leader) generate block and broadcast to other validators;
  Each validator receive the block and check its legality;
  if the new block is legal **then**
    audit and send the result including $<h, d, s>$ to each other, where h is height, d is hash of the block, and s is the signature of this node;
    if the received audit result $> (N-1)/3 + 1$ **then**
      Each node compare its work with others and send agree message to the leader $<h, d, s>$;
      if the leader receive agree message from more than $2(N-1)/3) + 1$ of nodes **then**
        Append the block to the global chain and broadcast to all nodes in the BET to store it in their local chain;
        Reward is distributed to the validators;
      else
        The leader request to nodes who sent disagree messages to check their audit once again;
      end if
    else
      Ignore
    end if
    if time expires and no consensus is reached **then**
      Abandon this consensus;
    end if
  else
    Discard the new block
  end if
end for

$$U_{TO_f}(\sigma, \tau) = \sum_{l \in N} \varrho_l \log_2 \left(1 + \frac{\sigma_l}{\tau_l}\right) - \sum_{l \in N} \phi_l \tau_l, \tag{28}$$

where $\varrho_l \log_2(1 + \frac{\sigma_l}{\tau_l})$ denotes the gain that TOs obtained from the mined transaction, ϱ_l is a positive coefficient used to convert the mined task obtainment earnings into monetary reward, and $\phi_l \tau_l$ refers to the cost incurred by the TO.

Besides, the mined task obtainment gain is an increasing function of σ_l and the log function indicates the satisfaction level of TOs. The TOs sets the unit price σ_l for task τ that validator l intends to mine. Also, other overhead cost ϕ incurred by TOs during maintenance, electricity, hardware loss and operation can be considered. Thus, the utility of TO is expressed as:

In the second stage, each validator EV $l \in \mathcal{N}$ strategies its mining task to maximize its own utility. The TOs' strategy is their reward, whereas each validator decides its participation based on the TOs' reward. The consensus plan of node l is represented by

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$\tau_l \geq 0$, i.e. the task it is willing to provide the mining service. We assume that each participating validator node is available during the consensus task, and all its activities are equally valuable to the consensus process. If consensus plan $\tau_l = 0$, it indicates that node l is not willing to participate in the block validation process. Let N validators are involved to validate task τ_l, the reward received by $\mathcal{N}_l$ is proportional to τ_l. Then the utility of $\mathcal{N}_l$ is calculated as:

$$U_{\mathcal{N}_l} = \frac{1}{N}\left(\sum_{l\in N}\sigma_l\tau_l - \sum_{l\in N}\lambda_l\tau_l\right), \tag{29}$$

where $\sigma_l\tau_l$ denotes the total reward validators obtained from the task τ_l that they validated and $\lambda_l\tau_l$ expresses the cost incurred by $\mathcal{N}_l$, λ_l denotes the mining cost vector with $\lambda = [\lambda_1, \lambda_2, \ldots, \lambda_N]^T$ is the set of unit mining costs. The optimization problems are formulated as a two-stage MLMF Stackelberg game below:

Stage 1: Leaders' Game(TOs' Pricing):

$$\begin{aligned} \max_{\sigma\geq 0} \quad & U_{TO_f}(\sigma_l, \tau_l) \\ \text{s.t.} \quad & \sum_{l=1}^{N}\tau_l \leq \Upsilon, \end{aligned} \tag{30}$$

Stage 2: Followers' Game (Validators' task mining):

$$\begin{aligned} \max_{\tau\geq 0} \quad & U_{\mathcal{N}_l}(\tau_l, \sigma_l) \\ \text{s.t.} \quad & U_{\mathcal{N}_l} > 0. \end{aligned} \tag{31}$$

Definition 2: Let σ^* and τ^* are the optimal price of TO and mining task demand of buyer, respectively, and the point (σ^*, τ^*) is the SE if satisfies the following.

$$U_{TO_f(\sigma^*,\tau^*)} \geq U_{TO_f(\sigma,\tau^*)}, \tag{32}$$

$$U_{\mathcal{N}_l(\sigma^*,\tau^*)} \geq U_{\mathcal{N}_l(\sigma^*,\tau)}. \tag{33}$$

Meanwhile, we use the second-order derivatives of the utility functions in Equations (28) and (29) with respect to σ and τ, respectively, to confirm the uniqueness and existence of the Nash equilibrium in our two-stage MLMF Stackelberg game.

$$\frac{\partial^2 U_{TO_f}}{\partial\sigma^2} = -\frac{2\,C}{\sigma^2}\frac{(N-1)U}{N} \leq 0, \tag{34}$$

$$\frac{\partial^2 U_{\mathcal{N}_l}}{\partial\tau^2} = -\frac{1}{n}\left(\frac{2\lambda}{\tau^2}\frac{(N-1)R}{N}\right) \leq 0. \tag{35}$$

Equations (34) and (35) show that U_{TO_i} and $U_{\mathcal{N}_l}$ are strictly concave. As a result, the Nash equilibrium exists in the formulated Stackelberg game. **Algorithm 3** shows the detailed process of the MLMF Stackelberg game-based incentive mechanism proposed to motivate block validators.

Algorithm 3: Stackelberg Game-Based Incentive Mechanism.

1: **Step 1:** The TO sets the initial unit price σ for task τ;
2: **Step 2:** Each validator submit its task plan;
3: **Step 3:** The TO checks the total number of validators planned to mine τ_l. Assume δ is small positive constant, $\mathcal{Q}$ is threshold and $\Delta\gamma$ is small step size;
4: **if** $\sum_{l\in N}\tau_l < (\mathcal{Q}-\delta)$ **then**
5: The TO increase the price by $\Delta\gamma$;
6: **else if** $\sum_{l\in N}\tau_l > (\mathcal{Q}+\delta)$
7: The TO decrease the price by $\Delta\gamma$;
8: **else**
9: The TO agrees to provide the task.
10: **end if**
11: **Step 4:** Step 2 and 3 are repeated until $|\sum_{l\in N}\tau_l - \mathcal{Q}| \leq \delta$;
12: **Step 5:** The validators perform mining tasks, while the TO transfers mining coins;

TABLE I
LIST OF KEY ABBREVIATIONS

Abbreviation	Description
EV	Electric vehicles
V2V	Vehicle-to-Vehicle
VEN	Vehicular Energy Network
IoEV	The Internet of Electric Vehicles
WPT	Wireless Power Transfer
BET	Blockchain-enabled Energy Trading
PPoR	PBFT-based PoR
MLMF	Multi-leaders and Multi-Followers
CH	Cluster Head
SC	Smart Contract
SM	Smart Meter
SDN	Software Defined Networking
ESU	Electric Storage Units
ECoin	Energy Coin
TO	Task owner

V. Performance Evaluation

A. Simulation Environment

This section presents the simulation scenarios deployed to evaluate the achievement of our proposed scheme using the benchmark schemes: PoW, PoS, PoR, and PBFT. We implement the simulations using Python 3.6 environment on a computer with a Core i7 CPU running on a processor speed of 2.4 GHz and 16 GB RAM. The simulation considers the standard parameters to assess a system's performance like throughput, latency, EV's utility, and scalability. We consider a V2V network that consists of three clusters connected with wireless links to a single MBS via RSU. The EVs are clustered based on their current location, speed, and direction. Each cluster has 10 to 30 seller and buyer EVs and 10 to 70 validator EVs. The diameter of each cluster is from 0 to 2 km. The RSUs have a transmission radius of 300 meters, and each EV has a speed range of 45 to 50 miles per hour, with a 22KWh charging rate [51]. The Euclidean distance between EV j and EV i range 5 to 100 meters and $\ell_{j.i}^{min}$ is set to 5 dB. The blockchain system is implemented with the Hyperledger Fabric blockchain. The energy block size is set at 1.0 MB, with a 0.42 seconds block propagation delay. The size of each transaction in the block ranges from 0 to 0.000573 MB. We consider TOs with a range of 5 to 30 and validators with a range of 10 to 70. The average transaction fee is set at 0.000062 ECoin. The simulation parameters are summarized in Table III.

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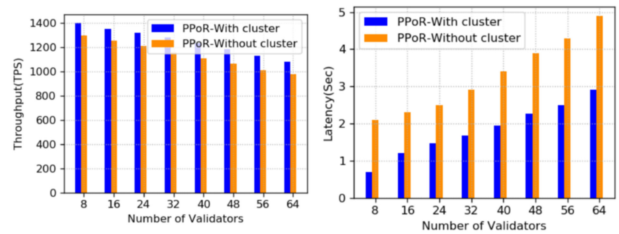
TABLE II
LIST OF KEY NOTATIONS

Notation	Description
$\mathcal{B}$	The set of energy buyers
$\mathcal{S}$	The set of energy sellers
$\mathcal{N}$	The set of validators
$\mathcal{E}$	The set of EVs in a cluster
$\mathcal{F}$	The set of TOs
α	Unit price of energy
η	Unit of energy purchased by the buyer
χ	Total available surplus energy of seller
μ	The energy demand of buyer
ψ	The cost incurred by seller
σ	The unit price of mining task
τ_l	Task mining plan of $\mathcal{N}_l$
Υ	The total available mining task of TO
λ	The cost incurred by the $\mathcal{N}_l$
ρ	The reputation value of validators
$\mathcal{Q}$	Max. validators expected to involve in verifying τ_l
δ	Small positive constant
$\Delta\gamma$	Small step size
ϕ	The cost incurred by validators to mine task τ_l

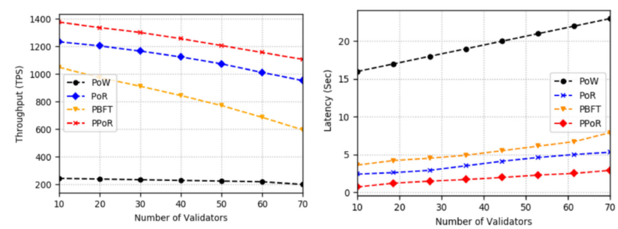
TABLE III
SIMULATION PARAMETERS

Parameters	Values
Number of EVs	[10-100]
Number of clusters	3
Location range of cluster	0-2km
Acceleration (min, max)	[0-5]
Speed range of EVs (min, max)	[45-50] miles/hour
MBS transmission radius	10 Km
RSU transmission radius	300 m
V2V charging rate	22 KWh
The block size	1.0 MB
Average block propagation delay	0.42 Sec
Reward for mining a block	10.88 ECoin
Transaction modelling technique	Full/Light
The average transaction propagation delay	5.1 sec
The average transaction fee	0.000062 ECoin
The average transaction size	0.000573 MB
The simulation length	2000 Sec



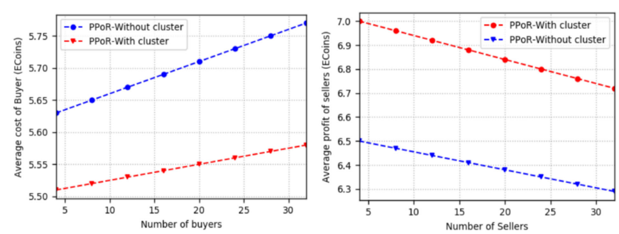
(a) (b)

Fig. 6. Analysis of performance in clustered and non-clustered scenarios. (a) Throughput. (b) Latency.



(a) (b)

Fig. 7. Throughput and latency comparison as a function of the number of validators. (a) Throughput. (b) Latency.



(a) (b)

Fig. 8. A comparison of buyer and seller utility in clustered and non-clustered scenarios. (a) Cost of buyers. (b) Profit of sellers.

B. Performance Analysis

The achievements of the PPoR consensus mechanism are evaluated in terms of throughput, latency, utility optimization, and scalability by considering three different scenarios.

First, we consider a clustered energy trading environment with an increasing number of buyers and sellers. Second, we assess the achievements of our proposed scheme in the non-clustered trading environment as the number of sellers and buyers increases. Finally, the achievement of PPoR is evaluated by comparing it with benchmarks such as PoW, PoR, and PBFT. The simulation results are analyzed as follows:

1) Throughput: It is the number of transactions processed by the nodes in a network commonly expressed as transaction per second (TPS). As the simulation results are shown in Fig. 6(a), deploying PPoR in a clustered scenarios increases throughput by 9.91% from non-clustered one and slightly decreases when the number of validators grows. Similarly, the simulation outcomes shown in Fig. 7(a) reveals that the PPoR scheme yields more throughput than PoW, PBFT, and PoR by 456.39%, 50.09%, and 12.75%, respectively.

2) Latency: It is the time difference between the energy request sent to the chain and the response received by the energy buyers. The simulation outcomes presented in Fig. 6(b) shows that the PPoR scheme decreases transaction processing latency by 44.22% when it is used in a clustered energy trading environment. Besides, as shown in Fig. 7(b), the transaction processing latency of PPoR is reduced by 90.60 %, 66.20 %, and 51.74 % compared to PoW, PBFT, and PoR, respectively.

3) Utility optimization: We evaluate the average profit gain of energy sellers and average cost energy buyers incurred to purchase energy.

The cost of energy buyers increases by 13.2% when the number of competitor vehicles grows in the system, as shown in Fig. 8(a). However, if the PPoR is used in a clustered energy trading scenario, the cost increment is not significant. As shown in Fig. 9(a), when we compare PPoR with other schemes, it performs better to optimize energy buyers' cost, where it decreases by 78.3%, 42.0%, and 21.1% from PoW, PBFT, and PoR, respectively. Fig. 8(b), on the other hand, shows that the gain of energy sellers increases as the number of buyers in the trading system grows and decreases when the number of

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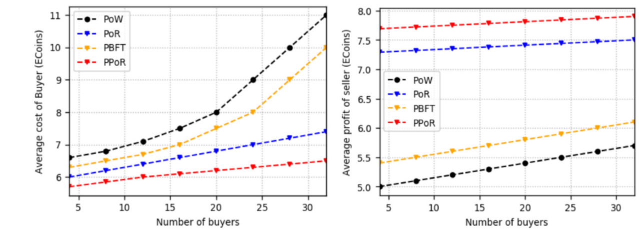
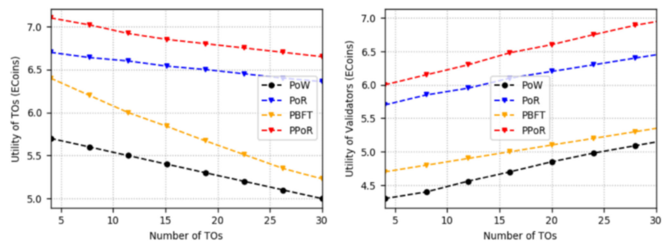


(a) (b)

Fig. 9. The profit of the seller and the cost of the buyer based on the number of buyers. (a) Average cost of buyers. (b) Average profit of sellers.



(a) (b)

Fig. 10. Analysis of the utility of TOs and validators as the number of TOs increases. (a) Utilities of TOs. (b) Utilities of validators.

sellers increases. Nonetheless, when PPoR is used in a clustered trading environment, the profit decreases slightly. As shown in Fig. 9(b), PPoR outperforms PoW, PBFT, and PoR to optimize energy sellers' profits by 42.1 %, 25%, and 18 %, respectively. The simulation results also show that the proposed scheme can effectively support buyers and sellers in energy trading to balance the cost and profit of both parties.

Furthermore, the effectiveness of the proposed incentive scheme is assessed in terms of utility optimization. We assessed the utility of TOs in light of the increasing number of TOs. Compared to PoW, PBFT, and PoR, the PPoR improves the utility of TOs by 28.01%, 19.10%, and 4.98%, respectively, as shown in Fig. 10(a). In addition, we evaluated the utility of validators in relation to the growing number of TOs. The simulation result shown in Fig. 10(b) shows that the PPoR scheme optimizes the utility of validators by 37.00%, 29.13%, and 6.5% over PoW, PBFT, and PoR, respectively.

4) Scalability: It can be measured in terms of transaction throughput and latency changes as the network size increases. Also, Fig. 6(a) and Fig. 7(a) shows that the throughput of PPoR and PoR decreases slightly with the increase of network size when we compare them with PBFT, yet in PoW, the throughput does not decrease significantly. However, the average throughput of PPoR is higher than the benchmark schemes. Furthermore, latency increases when the network size increase, as shown in Fig. 6(b) and Fig. 7(b). Our proposed scheme's transaction latency remains below 5 seconds when the network size increases from 10 to 70 EVs, while it is higher than 5 seconds in PoR, PBFT, and PoW. This shows that the PPoR consensus scheme is more scalable V2V energy trading than the benchmarks. Thus, the simulation results show that our scheme outperforms the benchmark schemes in all metrics used to compare their performance in the V2V energy trading system. Furthermore, the simulation results also show that the proposed scheme is more efficient under a clustered V2V energy trading scenario.

VI. Conclusion

In this paper, we proposed the PPoR consensus mechanism to improve the efficiency of V2V energy sharing in the IoEV. The consortium blockchain with SC is used to ensure the security and privacy of the V2V energy trading system. The entities participating in the trading process are clustered based on their mobility information to shorten the consensus process and balance node involvement in the block validation. The two-stage MLMF Stackelberg game is formulated to maximize the benefits of both sellers and buyers. In addition, we also proposed a Stackelberg game-based incentive mechanism that rewards monetary incentives and mining value for cooperating nodes while punishing misbehaving and malicious nodes to ensure the system's security. The simulation results show that the proposed method improves throughput, transaction latency, and utility optimization in the V2V energy trading. Furthermore, the PPoR scheme can ensure the security and scalability of energy sharing in the IoEV. Future work will improve the PPoR scheme by incorporating cryptography and machine learning techniques to enhance the system's privacy and efficiency.

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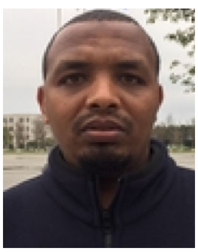

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