Path Planning for Energy Management of Smart Maritime Electric Vehicles: A Blockchain-Based Solution

Ahmed Barnawi, Shubhani Aggarwal, Neeraj Kumar, *Senior Member, IEEE*, Daniyal M. Alghazzawi, *Senior Member, IEEE*, Bander Alzahrani, *Member, IEEE*, and Mehrez Boulares

***Abstract*— Vehicle-to-grid (V2G) technology is used in the modern eco-friendly environment for demand response management. It helps in reducing the carbon footprints in the environment. However, security and privacy of the information exchange between different entities are significant concerns keeping in view of the information exchange via an open channel, *i.e.,* Internet among different entities such as plug-in hybrid electric vehicles (PHEVs), charging stations (CSs), and controllers in V2G environment. With an exponential rise in Electric vehicles (EVs) usage across the globe, there is a requirement of developing a seamless charging infrastructure for charging and billing. Moreover, secure information flow needs to be maintained at different levels in such an environment. Hence, this paper proposes a blockchain-based demand response management for efficient energy trading between EVs and CSs. In this proposal, miner nodes and block verifiers are selected using their power consumption and processing power. These nodes are responsible for the authentication of various transactions in the proposal. We also proposed a game theory-based solution to support energy management and peak load control off-peak and peak conditions. The proposed scheme has been evaluated using various performance evaluation metrics where its performance is found superior in comparison to the existing solutions in the literature.**

***Index Terms*— Vehicle-to-grid, electric vehicles, scheduling, blockchain, game theory.**

I. Introduction

THE use of traditional energy technologies such as coal power plants, fossil fuels *etc.*, at a large scale can lead to the mismanagement of demand response in modern smart eco-system. The burning of fossil fuels is the largest source of pollution causing increase of carbon dioxide (CO_2) in the environment. With this, thermal power plants (heat energy is converted into electricity) also produce CO_2. It is one of the most critical factors, which increases the concentration of greenhouse gases in the atmosphere, which causes global warming. Nowadays, the demand for energy generation from renewable energy resources such as solar energy, wind energy, hydro energy, tidal energy, geothermal energy, and biomass energy increases day-by-day [1]. However these energy resources are green, but having limitations of their uncertainty, volatile, and unpredicted nature. Even the integration of renewable energies with the smart grid is a challenging task [2], [3].

Manuscript received 30 April 2021; revised 12 August 2021 and 9 November 2021; accepted 24 November 2021. Date of publication 15 December 2021; date of current version 8 February 2023. This work was supported by the Institutional Fund Projects under Grant IFPHI-176-611-2020. The Associate Editor for this article was A. K. Bashir. *(Corresponding author: Neeraj Kumar.)*

Ahmed Barnawi, Neeraj Kumar, Daniyal M. Alghazzawi, Bander Alzahrani, and Mehrez Boulares are with the Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah 21589, Saudi Arabia (e-mail: ambarnawi@kau.edu.sa; nehra04@gmail.com; dghazzawi@kau.edu.sa; baalzahrani@kau.edu.sa; bmboulares@kau.edu.sa).

Shubhani Aggarwal is with the Department of Computer Science and Engineering, Thapar Institute of Engineering and Technology, Patiala 147004, India (e-mail: shubhaniaggarawal529@gmail.com).

Digital Object Identifier 10.1109/TITS.2021.3131815

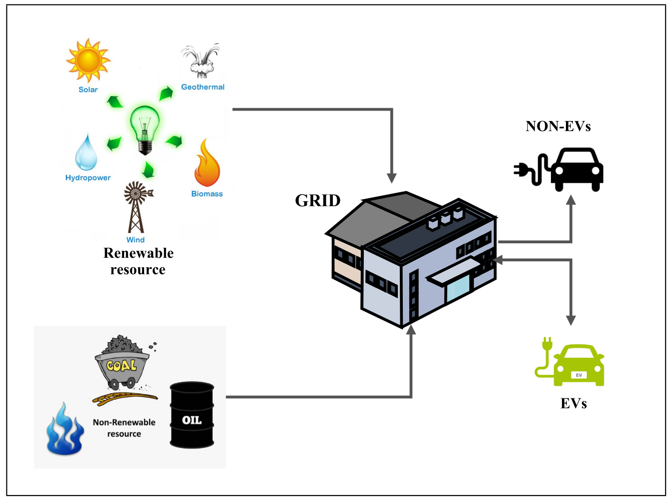

Fig. 1. Integration of renewable energy sources with EVs.

Though the energy generation from renewable energy resources is viable solution but it is not possible to completely utilize the ever-growing power demand. It may cause a mismatch between demand and supply, which is the root cause of grid instability. However, recently vehicle-to-grid (V2G) technology has been introduced to solve the demand response management problem in the smart grid. It is an emerging technology that integrates renewable energy systems with electric vehicles (EVs) [4], [5]. The overall power grid with renewable energy resources and conventional energy resources is as shown in Fig. 1.

EVs have been gaining popularity from the past few years because of their reduced dependency on fossil fuels, thus, contributing to a clean and green V2G environment in the V2G network. They also provides ancillary services to the grid by charging or discharging facilities with the power system. On the other hand, EVs can act as energy consumers and

1558-0016 © 2021 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission.
See https://www.ieee.org/publications/rights/index.html for more information.

Authorized licensed use limited to: CITY UNIV OF HONG KONG. Downloaded on April 15,2023 at 09:13:53 UTC from IEEE Xplore. Restrictions apply.

energy suppliers according to the requirements of the power grid system and contribute carbon dioxide-free environment. Hence, the battery of EVs may act as power storage to the electric motor. No extra generation capacity is required to charge the battery of the EVs [6]. Motivated by these, most of the countries across the globe have started the participation of EVs for ancillary services for a future green V2G environment [7]. EVs can reshape the transportation sector, drastically cutting carbon emissions and clearing the way for significant climate progress. However, they are still facing challenges on life cycle assessment, charger time and compatibility, availability of charging infrastructure, renewable energy and climate mitigation, and driving range compared to conventional fossil-fueled vehicles [8]. Moreover, there are several security and privacy vulnerabilities such as privacy-preservation, data manipulation, transparency, *etc.* in V2G environments. It may increase the gap between energy demand and supply. Hence, there is a requirement for demand response management scheme to stabilize the energy demand and supply.

From the above facts, we have observed that optimal participation of EVs in V2G requires not only for charging but also exceptional discharging of the EVs battery. By increasing the number of EVs, there is no control over power consumption, which may be a power mismatch between demand and supply, the primary cause of grid instability. It also causes uneconomical operations such as overloading, efficiency reduction, power quality, the voltage at the distribution side [9]. Therefore, serious problems may arise under uncoordinated charging/discharging scenarios of EVs. So, coordinated charging/discharging of EVs is a viable solution to mitigate all these problems. Many proposals exist on EVs participation to manage the charging/discharging operations for a green V2G environment [10]–[12]. For example, Li *et al.* [13] gave a comprehensive overview of the data analytics landscape on the EVs integration to green smart cities. They have discussed the solutions and need for data analytics for EVs integration to grid in smart cities. Similarly, Cai *et al.* [14] discussed the issues for reliable and efficient data exchanges between EVs, charging stations (CSs), and the power grid. They have provided the network design for hybrid vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication. Abedinia *et al.* [15] proposed a multiobjective-based optimization algorithm to solve the problem of EVs scheduling in a smart network because of sustainable energy sources based on the cost and pollution minimization. Similarly, Lin *et al.* [16]worked on mixed-integer linear programming (MILP) model, which considers green energy generation, energy storage, and EVs as a single-end user. They proposed an energy trading platform based on Internet-of-Energy (IoE) to reduce energy waste and maintain a green V2G environment. Hu *et al.* [17] proposed software-defined networking (SDN) architecture in a green V2G network for efficient and economical energy management. Similarly, Sun *et al.* [18] used an SDN for efficient and green EV charging management. The architecture includes three planes *i.e.,* application plane, control plane, and physical plane, presenting the demand side management approach for EV charging. Chen *et al.* [19] proposed an energy-efficient framework using pre-caching techniques in a blockchain-based IoT environment. Similarly, Raja *et al.* [20] proposed an intelligent reward-based data offloading in vehicular networks. They have used SDN controller to solve the dynamic optimization problem by performing an efficient offloading, which increases the overall system throughput.

From the facts mentioned above, we have observed that most of the researchers assumed the trusted third-party system in their design, which handles the EV's private information. So, security and privacy of EVs has been largely ignored. They have shared EV's private information to the central aggregator in their frameworks, leading to serious privacy concerns. Hence, there is a need for an efficient and secure energy trading framework for EVs charging in a green V2G environment. So, in this paper, we have designed a blockchain-based system model to provide efficient and secure energy trading between EVs and the CSs in a green V2G environment.

A. Contributions of This Paper

The major contributions of this paper are summarized as follows.

- A blockchain-based secure energy trading model for demand response management is proposed for a green V2G environment.
- A miner node selection scheme is presented using the power capacity and processing power of the entities present in the blockchain network.
- To efficiently manage the EVs in load management scenario, EVs are supposed to act as players using game theory and compete for acquiring energy from the CSs based on their respective utilities.
- In a peak load control scenario, EVs act as energy suppliers, *i.e.,* dual-mode EVs where they provide energy to other EVs as per their requirements. The batteries of the dual-mode EVs have considerable energy levels that choose either charging or discharging.

B. Organization

Rest of the paper is organized as follows. Section II discusses the related survey. Section III presents the system model for blockchain-based secure energy trading in a green V2G environment. Section IV discusses the proposed scheme with a detailed description of the algorithms. Section V describes the simulation results of the proposed scheme. Finally, the paper is concluded in Section VI.

II. Related Work

V2G technology has been gaining wide popularity in recent years. Many research articles focused on improving the grid performance. But, very few of these consider both the grid and EVs' preferences while developing charging/discharging algorithms in a green V2G environment [21].

In [22], authors proposed the EVs charging/discharging model to keep track of daily renewable generation. They have used the serial quadratic programming to optimal charging/discharging scheduling of EVs during 24 hours. Similarly, Rong-Ceng Leou [23] proposed an optimal charging/discharging control for EVs by considering the system constraints and operational costs. Jiang *et al.* [24] proposed

Authorized licensed use limited to: CITY UNIV OF HONG KONG. Downloaded on April 15,2023 at 09:13:53 UTC from IEEE Xplore. Restrictions apply.

the optimization model to coordinate renewable energy resources and the EVs to a minimum variance of equivalent load. Hadian *et al.* [25] proposed the optimal planning of EVs charging/discharging to peak shaving and valley filling. They have used multi-objective particle swarm optimization to control the rate and time of charging/discharging of EVs. Similarly, He *et al.* [26] proposed an optimal scheduling scheme for the charging/discharging of EVs. They have used convex optimization to minimize the total cost of EVs. In the same way, An *et al.* [27] focused on the charging/discharging strategy of EVs. They have considered the energy stored in EVs' batteries to support the high penetration of renewable EVs and enhance the power system's operational flexibility. Mehrabi *et al.* [28] proposed charging/discharging scheduling mechanism for EVs at home and joint lots for households prosumers. They have used the mixed optimization model to maximize consumers' profit and ensure the satisfaction of consumers. Similarly, Said *et al.* [29] also proposed a novel protocol based on queuing model for managing the charging/discharging of EVs in the smart grid. In the same way, Liu *et al.* proposed an optimization solution to optimize the route selection and charging/discharging scheduling of EVs. They have applied the artificial intelligence-based A* algorithm to find the shortest path for EVs. They have used the k-shortest-paths-joint-routing-scheduling for EVs to minimize the overall cost of the system in the V2G energy network.

From the literature, we have observed that no one has considered the security and privacy of EVs with charging/discharging facilities, which is a significant concern in a green V2G environment. There are several research articles where researchers have used the blockchain technology to provide security and privacy with the EVs charging/discharging facilities in a V2G environment [30], [31]. This technology is not only used in transportation systems but also used in various applications such as e-voting systems, smart grids, healthcare, aerial networks *etc.* [32]–[35]. For example, the authors in [36], [37] proposed an energy trading mechanism for EVs charging based on a blockchain to provide security and privacy in the system. Yang *et al.* [38] presented a blockchain-based virtual power plant for energy management to optimize system efficiency and preserve the users' privacy. Su *et al.* [39] proposed a contract theory for EVs charging in an intelligent community secured by permission blockchain. Similarly, Samuel *et al.* [40] proposed a blockchain approach to resolve the privacy issue without restricting trading activities in V2G networks. Gao *et al.* [41] proposed a blockchain-based privacy-preserving payment mechanism that enables data sharing while securing sensitive user information in V2G networks. In a similar way, Radi *et al.* [42] proposed a blockchain-based system where energy traders and EVs owners work together to satisfy EVs' energy demands with the privacy-preservation of EVs. Li *et al.* [43] proposed an optimal secure and privacy-preserving trading scheme for charging/discharging scheduling of EVs. They have implemented the proposed work on Hyperledger Fabric that evaluates the scalability of the scheme. Similarly, Li *et al.* [44] proposed a scheduling scheme for two-way energy trading between EVs and the smart grid. They have used the improved krill herd algorithm to improve the power load fluctuations and implemented it on Hyperledger to evaluate the feasibility and effectiveness of the system. Liu *et al.* [45] proposed a blockchain-based EV charging scheme based on a genetic algorithm to minimize the load fluctuation level and overall charging cost for EVs in the smart grid. They have used the Iceberg order execution algorithm to improve the EVs charging/discharging scheduling. Moreover, Abdullah Yildizbasi presented the blockchain for the transformation in the energy sector and ensured the sustainability of energy grid management systems [46]. In addition, Xu *et al.* [47] proposed a blockchain-based power dispatching framework for high renewable energy penetrated power systems. They used this model to protect the interests of low-carbon technology users that improve the grid's stability and reduce the abandoned renewable energy sources generation. Nevertheless, no one has described the EVs scheduling concerning charging/discharging facilities using blockchain in a green V2G environment. Hence, in this paper, we propose a blockchain-based energy trading model for demand response management. Then, we have discussed the energy management and peak load control scenarios to efficiently and effectively manage the EVs charging/discharging facilities during peak and off-peak conditions.

The comparison of the proposed energy trading scheme with the existing schemes is shown in Table I.

III. System Model

This section discusses a general scenario of a green V2G environment in the smart grid for demand response management. It comprises EVs and CSs entities, which are connected in a blockchain network where EVs act as energy consumers and energy suppliers and CSs act as energy suppliers. The energy trading between the entities is so that one wants to sell energy, and the other wants to buy it. The proposed system model is as shown in Fig. 2, and its working is described as follows. Initially, the nodes communicate the charging/discharging energy requests on a blockchain. Then, these requests are passed to all the nodes present on a blockchain. Under peak and off-peak conditions, energy trading takes place between the entities for demand response management. There is a power line communication between EVs and CSs. Most EVs are equipped with an onboard charging system that converts grid-supplied alternate current (AC) to the direct current (DC) required for EVs charging. These onboard chargers enable a vehicle to be charged directly from a standard home plug (slow AC) at home, workplace, or public location. Some CSs provide direct current to the EVs and bypass the onboard converter are referred to as DC chargers. Due to the ability of fast charging, it provides higher charging rates. The CSs have some intelligence that takes care of EVs authentication and communication, data collection and monitoring, and payment. After the successful trading, the energy coins are transferred from the buyer's wallet address to the seller's wallet address on a mutually agreed value. The detailed description of system model entities is explained as follows.

A. Electric Vehicles

EVs play a vital role in a V2G environment. It has the capability of bi-directional energy trading. It can act as an energy producer and provide electricity by discharging its battery

Authorized licensed use limited to: CITY UNIV OF HONG KONG. Downloaded on April 15,2023 at 09:13:53 UTC from IEEE Xplore. Restrictions apply.

TABLE I
COMPARISON BETWEEN THE PROPOSED ENERGY TRADING SCHEME WITH THE EXISTING SCHEMES

Reference	Description	Blockchain Used	EVs scheduling	Consensus	Miner node selection	Data set
[25]	Multi-objective particle swarm optimal allocation of EVCS with charging/discharging scheduling	×	✓	×	×	IEEE 69 bus
[26]	Covex optimization-based optimal scheduling for charging/discharging of EVs	×	✓	×	×	Real base load in Toronto on Aug, 2009
[27]	Security-constrained optimal charging/discharging of EVs with high renewable penetration	×	×	×	×	Case study for Jeju island in South Korea
[28]	Mixed optimization of charging/discharging scheduling of EVs at home and common lots	×	✓	×	×	-
[29]	Queuing model for charging/discharging management protocol for EVs	×	✓	×	×	1000 EVs & 20 EVSEs
[39]	Contract theory with secure charging scheme for EVs	✓	✓	×	×	100 EVs in smart community
[43]	krill herd algorithm based charging discharging trading scheme for EVs	✓	✓	×	×	10 peer, 3 zookeeper, 4 kalka, & 3 ordered nodes
[44]	improved krill herd-based iterative two-layer optimization for charging/discharging of EVs	✓	✓	×	×	IEEE 30-node test system
[45]	Iceberg order execution-based adaptive blockchain-based EV participation scheme	✓	✓	×	×	Toyota Prius & Tesla model
Proposed Scheme	Path Planning for Energy Management of Smart Maritime EVs	✓	✓	PoW	✓	Smart grid lab & Us open datasets

during peak time. On the other side, it can also act as an energy consumer by charging its battery with electricity during the peak-off time. They can adjust their charging and discharging nature and actively participate in a green V2G environment. In this paper, as a decentralized blockchain-based system, EVs communicate on a blockchain for charging/discharging the battery. Those EVs who need electricity services can determine their service demand to purchase the energy on a blockchain. They take energy services from the CSs and the other EVs in a particular time slot.

- *EV's as Energy Consumers:* When EVs act as energy consumers, the maximum amount of energy an EV 'EV_i' can buy is depends upon the state of charge level. If available state of charge of an EV_i is 'SC_i^{avl}' while maximum state of charge is 'SC_i^{max}', then the state of charge that can be charged (SC_i^{chr}) is:

$$SC_i^{chr} = SC_i^{max} - SC_i^{avl} \tag{1}$$

The corresponding energy needed 'EV_i^{need}' that can ge given to EV_i is:

$$EV_i^{need} = SC_i^{chr}.E_i^{rated} \tag{2}$$

where, E_i^{rated} is the rated energy capacity of EV_i. And the amount EV_i has to pay in return to take the charging energy from the seller is defined as.

$$Amt(EV_i \rightarrow seller) = EV_i^{need}.P_p' \tag{3}$$

where, P_p' is the amount or price announced by the seller to sell the energy to EV_i [48].

- *EV's as Energy Suppliers:* When EVs act as energy suppliers, they can also give energy to the EVs during peak timings. So, the excess energy at EV_{dual} after giving the energy to EVs is:

$$E_{dual}^{exc} = E_{dual}^{avl} - EV_i^{need} \tag{4}$$

Also, the following condition should satisfy to give energy to EVs is:

$$E_{dual}^{avl} \geq EV_i^{need} \tag{5}$$

Moreover, for the successful energy trade, the price announced by the dual-mode EV must be accepted by buyer EV before the trade may take place. If the dual-mode EV charges price p_{dual}, then the buyer EV has to pay equals to the amount:

$$Amt(EV_i \rightarrow EV_{dual}) = EV_i^{need}.p_{dual} \tag{6}$$

B. Charging Stations

A charging station is a piece of equipment that connects an EV to a source of electricity to recharge its batteries. Some CSs have advanced smart metering, cellular capability, and network connectivity, while others are essential features. They are also called electric vehicle supply equipment (EVSE).

Authorized licensed use limited to: CITY UNIV OF HONG KONG. Downloaded on April 15,2023 at 09:13:53 UTC from IEEE Xplore. Restrictions apply.

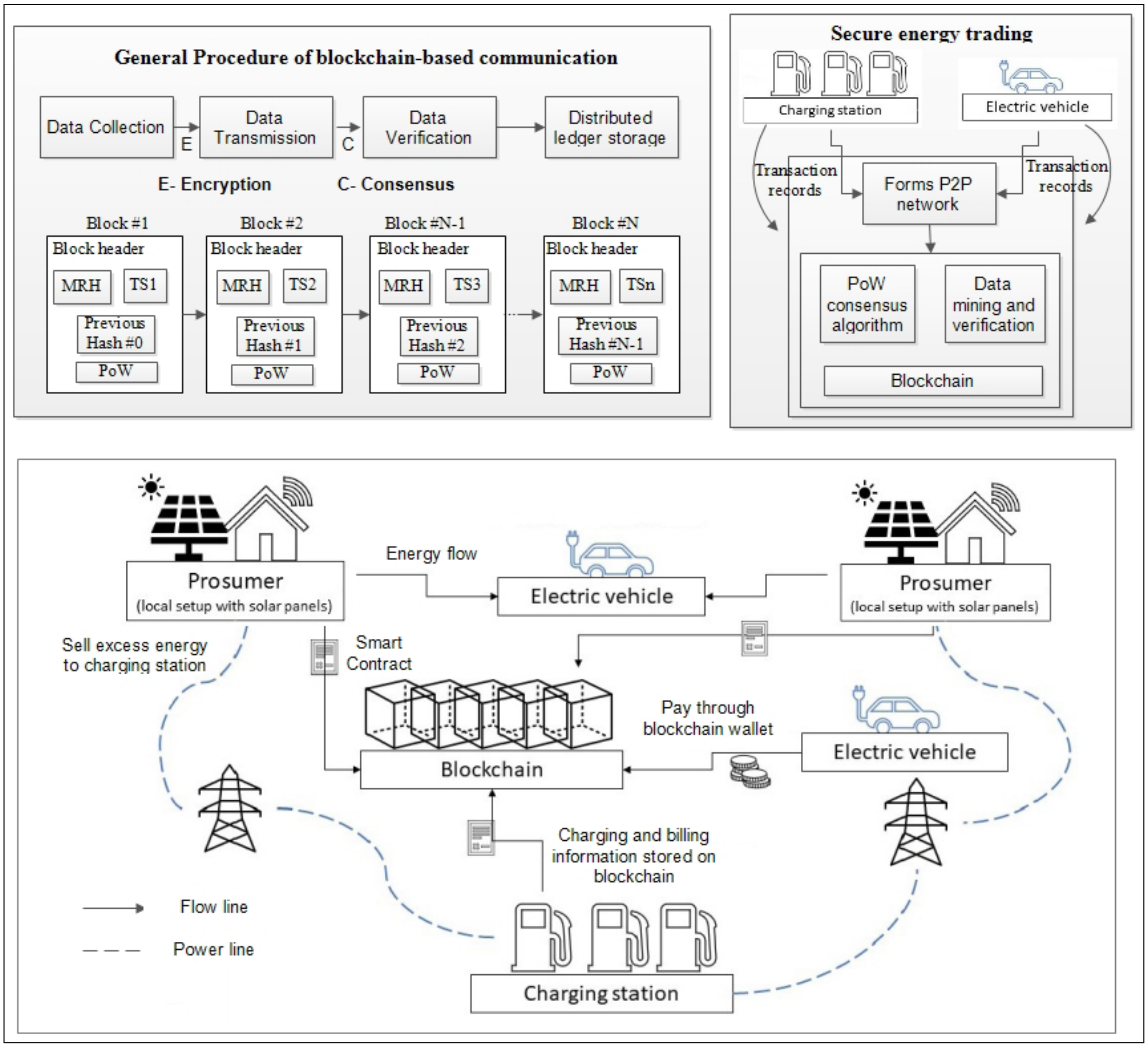

Fig. 2. System model.

They are provided in municipal parking locations by electric utility companies or at retail shopping centres by private companies. These stations provide special connectors that conform to the variety of electric charging connector standards. In this paper, we have considered several CSs that provide energy to EVs as per-kWh. They act as energy suppliers, which give energy to EVs under peak and off-peak timings. During off-peak timings, the rate of discharging energy by CSs is the same, but in peak timings, it can vary from one CS to the other. If the energy given to EV_i by CS_j is EV_i^{need} and CS_j has available energy is E_j^{avl}, then excess energy at CS_j is given by,

$$E_j^{exc} = E_j^{avl} - EV_i^{need} \tag{7}$$

The condition should be satisfied that the required or needed energy by EV_i from the CS_j must be:

$$EV_i^{need} \leq E_j^{avl} \tag{8}$$

C. Blockchain Network

The operation of a blockchain-based energy trading scheme for demand response management between the entities is described as follows. The blockchain mechanism provides privacy to the associated entities by using cryptographic primitives to authenticate the transactions amongst these entities [49], [50]. It is referred to as a continuous chain of data blocks containing the nodes' information. In this system, each node has its ledger to maintain the history of transactions. There are two types of nodes presented in the system model, as shown in Fig. 2. The first is the miner node, and the other is the normal node. The miner nodes are responsible for authenticating and authorizing the transactions the users want to perform securely. In contrast, normal nodes maintain a ledger to keep the logs of their transactions.

The blockchain network designs a scheme, which specifies the relationship between the entities, *i.e.,* the amount of energy needed by EVs and the reward, *i.e.,* payment to the seller in terms of energy coins [51]. In this scheme, each node on the network sends a request for charging/discharging the energy. The energy buyer nodes are requesting to charge the batteries. On the other hand, energy selling nodes are requesting discharging on the blockchain network. They compete among themselves for making an energy transaction with

Authorized licensed use limited to: CITY UNIV OF HONG KONG. Downloaded on April 15,2023 at 09:13:53 UTC from IEEE Xplore. Restrictions apply.

maximum utility. A reward or penalty process is done as per their scheduling time-slots. So, this scenario is based on the game formulation. Every action of the game on the network stores it on the public ledgers of the nodes. After completing the energy transaction, an energy seller will receive an energy coin from the corresponding charged EVs. The authentication of the payment can be verified by checking the last block of the blockchain.

All the energy transactions between the entities have been collected and recorded within a certain amount of time. Then, these transactions are encrypted, digitally signed, and structured into blocks. Further, these blocks are broadcasted on the blockchain network for verification and validation, which is done by Proof-of-Work (PoW) [52]. Fake and invalid transactions will be discarded. Each node on the network competes to create a block by solving the complex mathematical puzzle and creating a hash value. The computed hash value from the puzzle consists of a nonce *'N'* (a random number), the previous hash *'h'* of the block, timestamp *'T'*, and other data. A valid *'N'* satisfies the $(\alpha + h) < \beta$, in which β represents the difficult level. The first node that finds the valid PoW broadcasts it on the network for validation. All the other nodes audit and validate the PoW. If the received PoW is valid by all the nodes (consensus has been reached when 51% nodes satisfy on PoW), the block is added to the chain; otherwise, not. The node which created the block will be rewarded with a certain amount of bitcoins. So, in a nutshell, the blockchain mechanism in the system model works in the following steps.

1) The requesting entities float an energy transaction charging/discharging request in the blockchain network.
2) The requests are then passed onto the miner nodes for authentication. These nodes add the transaction to a blockchain when the calculated hash is similar to the received hash.
3) If the requests are authentic, the miner node sends these requests to all other entities to store the transaction history.
4) Both charging/discharging requests are segregated for energy management and peak load control scenarios. Then, the actual energy trade happens between the entities.
5) The energy coins are transferred from the buyer's wallet address to the seller's wallet address. The miner node then authenticates the wallet address using a PoW mechanism. It transfers the amount once its wallet is successfully authenticated.

IV. Proposed System

In this section, we present the working of the proposed scheme by involving several EVs and CSs for real-time management of load in a green V2G environment. Initially, the miner node is selected to validate the blocks created during the energy transactions between the blockchain entities. After the block validation, the trading between them takes place based on the energy requirements. The energy demands by the entities may vary concerning time and hence may cause energy fluctuations on the network. Therefore demand response management is used to balance the energy demand and supply between the entities. This method is utilized to schedule EVs during off-peak and peak timings that supports energy management and peak load control, respectively. However, EVs are reserved for both charging/ discharging and CSs for discharging purposes during energy transactions.

Once the requests are received at the blockchain network, these requests are segregated into charging requests and discharging requests. Hence, charging requests are scheduled to support energy management, whereas discharging requests of EVs are scheduled to support peak shaving. In other words, there is a need for time slots to schedule the EVs during peak and off-peak timings. The algorithms for miner nodes selection, energy management, and peak load control are described below, which have been used to address the energy trading scheme for demand response management.

A. Miner Node Selection

The miner nodes are selected so that all the EVs and the CSs present on a blockchain may become the miner nodes. Initially, the number of EVs and CSs are given as inputs that output the miner nodes' selection. For selecting the miner nodes from all the entities, we use different criteria for different entities. In the case of CSs, their power capacity is taken into account for selecting miner nodes. The power capacity which has more value than the threshold value 'TH_{CS}' is put in the list '$List$'. With this, we have considered the stake values S_{CS} of CS and its threshold value is S_{Th} as mentioned in the Algorithm 1. Similarly, in the case of EVs, their processing power and stake values are taken into consideration used for validation purpose in the mining process and those EVs have more processing power and stake values than threshold value 'TH_{EV}' and S_{Th}, respectively are put in the list '$List$'.

Finally, for the selection of miner nodes, the ratio of miner nodes to the normal nodes (β) is considered based on how many miner nodes are selected from the $List$. In the proposed scheme, the value of beta is set as 20%. The advantage of selecting miner nodes is that even if one entity tries to maximize its power for becoming a miner node. Then, also it is not sure that it will become miner nodes. So, every node on a blockchain would stay true to its true nature. In addition to it, the values of TH_{CS} and TH_{EV} are changed after periodic intervals of time, so each node has an equal chance to participate in the miner node selection process. The algorithm is then executed again, and new miner nodes are selected based on the changed threshold values. This makes the energy management scheme for demand response management more robust and helps avoid an adversary who tries to find out the miner nodes and attempt to manipulate them.

B. Demand Response Management

Game theory involves the interactions among different players which are participated in the game [53]. Each player plays a different game strategy while considering the game rules and maximizing its payoff. This theory can be divided into two main categories, *i.e.,* cooperative and non-cooperative. In the cooperative game theory, players coordinate with one another to maximize their payoffs. In contrast, in the non-cooperative game theory, players do not interact and play the

Authorized licensed use limited to: CITY UNIV OF HONG KONG. Downloaded on April 15,2023 at 09:13:53 UTC from IEEE Xplore. Restrictions apply.

Algorithm 1 Selection of a Miner Nodes

Input: Number of electric vehicles 'N' and charging stations 'M'
Output: Miner Node 'MN'

procedure FUNCTION($MINER\_NODE\_SELECTION$)
  /*For the blockchain nodes Charging Stations 'CS' */
  Set threshold value = TH_{CS}
  for ($CS = 1$; $CS \leq size(M)$; $CS++$) **do**
    Get the power capacity 'P_{CS}' of each 'CS'
    Get the stake value 'S_{CS}' of each 'CS'
    if ($P_{CS} \geq TH_{CS}$ && $S_{CS} \geq S'_{TH}$) **then**
      Put 'CS' in list '$List$'
    end if
  end for
  /*For the blockchain nodes Electric Vehicles 'EV' */
  Set threshold value = TH_{ev}
  for ($EV = 1$; $EV \leq size(N)$; $EV++$) **do**
    Get the processing power 'P_{EV}' of each 'EV' used for validation
    Get the stake value 'S_{EV}' of each 'EV'
    if ($P_{EV} \geq TH_{EV}$ && $S_{EV} \geq S_{TH}$) **then**
      Put 'EV' in list '$List$'
    end if
  end for
  Compute number of miner nodes, $MN = \beta * size(List)$ ▷ β represents the ratio of miner nodes to normal nodes
  Randomly select the 'MN' from list $List$ and make them miner nodes
end procedure

game for individual payoffs. In this paper, the nodes on the blockchain network act as players that plays a non-cooperative game. Here, EVs on a blockchain calculate their payoff values to complete for an energy resource CS and try to maximize its payoff on its own. The auction game theory is applied in energy management when two or more EVs have the same payoff value. Then, according to the *sealed-bid first-price auction*, EV pays higher to CS can schedule first at CS for charging the battery. The players once announce their prices can not change, and the other players are not aware of the prices announced in encrypted or sealed form.

Hence, the proposed energy trading scheme for demand response management has been optimized based on energy coins and the state of charge. Accordingly, a payoff (μ) value is calculated for EV_i in the following equation 9 that supports load management during off-peak timings.

$$\mu_i = SC_i^{EV}.a_1 + EC_i.b_1 \tag{9}$$

where EC_i is the new energy coins; SC_i^{EV} is the state of charge; a_1, b_1, are the constant values.

The charging energy capacity (EV_i^c) of EV_i battery changes according to its quality of degree d as mentioned below.

$$EV_i^c = (EV_i^{need})/d \tag{10}$$

1) Energy Management in Demand Response Management: Algorithm 2 describes the working of demand response management in V2G environment, as follows. Initially, the EVs that require charging energy request for acquiring energy on the blockchain network. All the requests have been stored in the list 'L' represents (line 2). Then, calculate the payoff value (μ_p) (as calculated in equation 9) and corresponding needed energy (EV_i^{need}) of the EVs and store this information in structure K_p (lines 3-6). Further, the structure of K_p is sorted in descending order from the highest payoff value to the lowest (lines 7-15). After sorting, select J_p of highest payoff from the K_p that subjects CSs resource having same energy

Algorithm 2 Energy Management

Input: n: Charging requests by the EVs on a blockchain.
Output:List of the EVs used for load management.

1: **procedure** FUNCTION(EM)
2:   Store all requests of the EVs for charging in the List 'L'.
3:   **for** ($p = 1$; $p \leq n$; $p++$) **do** ▷ Calculate payoff value
4:     Calculate μ_p
5:     Store μ_p and corresponding E_p in the structure K at K_p
6:   **end for**
7:   **for** ($p = 1$; $p \leq n$; $p++$) **do** ▷ Sort K according to the μ_i in the descending order
8:     q ← p
9:     **while** (q > 0 && $K_{q-1} < K_q$) **do**
10:       temp ← K_{q-1}
11:       $K_{q-1} \leftarrow K_q$
12:       $K_q \leftarrow$ temp
13:       q ← q-1
14:     **end while**
15:   **end for**
16:   **for** ($p = 1$; $p \leq m$; $p++$) **do** ▷ m is the number of CSs
17:     $J_p \leftarrow K_p$
18:   **end for**
19:   J maintains the list of the EVs that succeed to take charging from the available CSs
20:   Select J_p which has highest μ_p
21:   Subject CSs to charge the battery of J_p based on battery requirements.
22:   **for** ($j = 1$; $j \leq m$; $j++$) **do**
23:     E ← E_j^{avl} ▷ E_j^{avl} is the current energy of J_p
24:     **for** ($i = 1$; $i \leq p$; $i++$) **do**
25:       **if** $E \geq EV_i^{need}$ **then** ▷ J_p need EV_i^{need} energy
26:         E_j^{exc} = E - EV_i^{need} ▷ Excess energy after charging an EV
27:       **end if**
28:     **end for**
29:   **end for**
30:   L' ← J_p
31:   Return L' ▷ L' represents the list of charged EVs
32:   **while** ($K_{p+1} == K_p$) **do**
33:     $J_{p+1} \leftarrow K_{p+1}$
34:   **end while**
35:   $t \leftarrow p$
36:   **while** ($J_{t-1} == J_t$) **do**
37:     $k \leftarrow k + 1$ ▷ k represents number of EVs having same μ
38:     $t \leftarrow t - 1$
39:   **end while**
40:   $M \leftarrow m - (p - k)$ ▷ M number of top bidders
41:   **for** ($j = 1$; $j \leq k$; $j++$) **do**
42:     Do sealed bid auction for EV_j
43:     $L \leftarrow EV_j$
44:   **end for**
45:   Select first 'M' EV having maximum bid
46:   **for** ($p = 1$; $p \leq m$; $p++$) **do**
47:     Select L_i to charge upto m EVs
48:   **end for**
49:   **for** (k = m+ 1; k ≤ n; k ++) **do**
50:     Schedule EVs for other time-slots
51:   **end for**
52:   Give energy coins (EC) to the CSs from the charged EVs
53: **end procedure**

price, allocate to the EVs for charging the battery (line 16-21). J_p maintains the list of EVs that succeed in outperforming other EVs in the game and can now be considered for scheduling during energy management. E_j^{avl} represents the available energy at CS. The algorithm then identifies the EVs that can be allocated time slots at CSs for charging. This information is maintained in list L' (lines 22-31). There can arise a situation where two or more EVs may have the same payoff value and require the same amount of state of charge for charging. The energy request of such EVs is resolved by the following method. Firstly, such EVs are identified (lines 32-39), and then bidding is performed by them to charge first among these EVs. Sealed-bid first-price auction is used in this approach (lines 40-44) and then CS resources are reserved to only top m EVs in L (lines 45-48). EVs that were not

Authorized licensed use limited to: CITY UNIV OF HONG KONG. Downloaded on April 15,2023 at 09:13:53 UTC from IEEE Xplore. Restrictions apply.

Algorithm 3 Peak Load Control

Input: n: requests for discharging energy $(E_{dual})_j^{dis}$ by EV_j^{dual}
Output: Select the EV_j^{dual} used for peak shaving.

1: **procedure** FUNCTION(PKC)
2: **for** $(j = 1; j \leq n; j++)$ **do** ▷ Sort list P according to price $p_j^d ual$ announced by EV_j^{dual}
3: q ← j
4: **while** (q > 0 && $P_{q-1} > P_q$) **do**
5: temp ← P_{q-1}
6: $P_{q-1} \leftarrow P_q$
7: $P_q \leftarrow$ temp
8: q ← q-1
9: **end while**
10: **end for**
11: $E_i \leftarrow EV_i^{need}$
12: **if** $(m \leq n)$ **then** ▷ compare m, and n
13: k ← m ▷ m equals number of EVs
14: **else**
15: k ← n
16: **end if**
17: **for** $(j = 1; j \leq k; j++)$ **do**
18: **for** $(i = 1; i \leq k; i++)$ **do**
19: $E \leftarrow (E_{dual})_j^{dis} - E_i$ ▷ E represents the excess energy of EV_{dual}
20: L ← EV_j^{dual}
21: **end for**
22: **end for**
23: **for** $(l = k + 1; l \leq n; l++)$ **do** do
24: Schedule EV_j^{dual} for other time or for other EVs
25: **end for**
26: Return L ▷ L represents the list of EV_{dual} that already used for discharging
27: Give energy coins (EC) to the EV_{dual} from the charged EVs
28: **end procedure**

scheduled during the considered time slot are scheduled later having energy requirement (lines 49-51). In the last, after the completion of energy transactions, the energy coins EC are transferred from EVs wallet address to CSs wallet address. All the information is stored on the blockchain network for transparency and immutability of the system model.

2) Peak Load Control in Demand Response Management: Under peak conditions, dual-mode EVs provide the energy to manage the high demand for charging the battery of EVs. The energy is drawn from dual-mode EVs having an excess state of charge (as described in equation 5). This excess state of charge should be greater than or equal to the energy needed by EVs (in equation 6). This subsection elaborates the allocation of dual-mode EVs to the energy-required EVs under demand response management.

The energy that dual-mode EVs EV_{dual} can discharge is E_{dual}^{dis}, which has been used to charge the EVs is presented in the following equation 11.

$$(E_{dual})_j^{dis} = (SC_{dual})_j^{dis}.E_{rated(EV_{dual})} \tag{11}$$

The actual energy according to the quality of degree (d) that the EV_{dual} can discharge is presented in the following equation 12.

$$(E_{dual})_j^{dis} = d(SC_{dual})_j^{dis}.E_{rated(EV_{dual})} \tag{12}$$

where, $(E_{dual})_j^{dis}$ is the energy discharge by EV_{dual}; $(SC_{dual})_j^{dis}$ is the state of charge; $E_{rated(EV_{dual})}$ is the rated capacity of the EV_{dual} in kilowatt-hour (KWh).

The algorithm 3 defines the working of peak shaving for demand response between the dual-mode EVs and the charging energy requires EVs. All the dual-mode EVs sending the discharging energy request with their submitted bid price 'p_{dual}' on the blockchain network. This information can never be changed because of the immutability nature of blockchain and the other dual-mode EVs are not aware of the prices announced as it is in encrypted or sealed form. In this algorithm, the list of the dual-mode EVs with respect to the cost per unit of energy C_j^d and energy discharge $(E_{dual})_j^{dis}$ by the EV_j^{dual} are maintained in the ascending order to the list 'P' and 'Q', respectively. In the same manner, the first (2-10) lines of the algorithm represent the sorted list of the EV_j^{dual} according to the price $p_j^d ual$ announces by the EV_j^{dual} on the blockchain. Line (11) represents the energy needed (EV_i^{need}) by the EVs to fulfill the charging requirements. If m is less than n, then variable k is updated with a value of m; otherwise n (lines 12–16). After this, the dual-mode EVs are selected from 'P' one by one until all the EVs' energy requirement is fulfilled and they are scheduled (lines 17–22). The dual-mode EVs in P, which was not scheduled during the considered time slot is either scheduled at later time slots or are redirected to other EVs having peak shaving requirements (lines 23–27). Similarly, here, all the information is stored on the blockchain network and the energy coins are transferred from EVs to the dual-mode EVs' wallet address after successful energy trading between them.

C. Payment Process

Players are also given a payment based on the actions performed by them during the game. This process has two different scenarios; one for reward and another for a penalty. The rewards are described for those EVs who have taken energy from the CSs at their respective time slots and penalties for those who have failed to arrive on their respective time slots. The reward-penalty equation 13 between them in terms of energy coins EC_i is shown below.

$$EC_i = \begin{cases} SC_i^{chr}.C_i^d.\alpha + EC_i^{old}.\beta \rightarrow reward \\ EC_i^{old}.\gamma \,|\, \gamma \,\epsilon (0,1) \rightarrow penalty \end{cases} \tag{13}$$

where α, β, γ are the constant parameters; SC_i^{chr} is the state of charge that the EV_i draws from the CS_j; C_i^d is the cost offered by CS_j to charge the battery; EC_i^{old} denotes the energy coins of EVs until the previous iteration.

Some EVs have the capability to be involved in charging or discharging since they have sufficient amount of state of charge called the dual-mode EVs. Their state of charge SC^{dual} ranges between the minimum and maximum limits is as shown in equation 14.

$$SC_{min}^{dual} < SC^{dual} < SC_{max}^{dual} \tag{14}$$

where, SC_{min}^{dual} and SC_{max}^{dual} are user-defined values of the state of charge for EVs as per the requirements.

D. Complexity Analysis

The complexity analysis in terms of time complexity (TC) and space complexity (SC) of the proposed algorithms is described as follows.

1) Time Complexity: In Algorithm 1, power capacity is computed for *m* CSs that takes *O(m)* time. After this, the processing power is computed for *n* EVs that also takes *O(n)* time. The assignment operators take linear time. Hence, TC of this algorithm is given as follows:

$$TC = O(m) + O(n) \tag{15}$$

Authorized licensed use limited to: CITY UNIV OF HONG KONG. Downloaded on April 15,2023 at 09:13:53 UTC from IEEE Xplore. Restrictions apply.

In Algorithm 2, μ_p is computed for n EVs that takes *O(n)* time. After this, a list of n EVs is sorted using insertion sort, which consumes $O(n^2)$ time. Lines 16–18 take linear time as these are assignment operations. From the ordered list of EVs, the selection of confirmed time-slot EVs at CSs consume $O(n^2)$ time (lines 22–31). The resource reservation of selected EVs takes *O(n)* time. Hence, TC of this algorithm is given as follows:

$$\begin{aligned} TC &= O(n) + O(n^2) + O(n^2) + O(n) \\ TC &= O(n^2) \end{aligned} \tag{16}$$

In Algorithm 3, the list P using insertion sort with the worst-case complexity is $O(n^2)$. Assignment statements take *O(1)* time. The computation, and scheduling of EVs takes *O(n)* time. Thus, the TC of this algorithm is given as follows:

$$\begin{aligned} TC &= O(n) + O(n^2) + O(1) \\ TC &= O(n^2) \end{aligned} \tag{17}$$

2) Space Complexity: In Algorithm 1, there is a total of two lists and one structure. The size of these lists and structure cannot exceed n, *i.e.*, the number of EVs. Hence, SC of this algorithm is given as follows:

$$\begin{aligned} SC &= O(n) + O(n) \\ SC &= O(n) \end{aligned} \tag{18}$$

In Algorithm 2, there is a total of two lists and one structure. The size of these lists and structure cannot exceed n, *i.e.*, the number of EVs. Insertion sort used in the algorithm takes minimum space complexity of *O(n)*. The rest of the algorithm uses assignment, calculation, and scheduling steps, which takes *O(1)* space. Hence, SC of this algorithm is given as follows:

$$\begin{aligned} SC &= O(n) + O(n) + O(n) + O(n) + O(1) \\ SC &= O(n) \end{aligned} \tag{19}$$

In Algorithm 3, sorting takes space complexity of *O(n)*. A total of four lists have been used that take space of *O(n)*. All other calculations and assignments take *O(1)* space. Hence, SC of this algorithm is given as follows:

$$\begin{aligned} SC &= O(n) + O(n) + O(n) + O(n) + O(n) + O(1) \\ SC &= O(n) \end{aligned} \tag{20}$$

V. Results and Discussion

This section presents the simulation results and security evaluation of the proposed energy trading model. The parameters used for simulation is described in Table II.

A. Numerical Results

This section presents the simulation-based numerical results along with discussions about the results obtained. In the case of energy management scenario, the considered EVs that required charging energy compete with each other based on their payoff values, which further depends on the state of charging and energy coins (as mentioned in equation 9).

$$\mu_i = SC_i^{EV}.a_1 + EC_i.b_1 \tag{21}$$

TABLE II

Simulation Parameters

Parameters	Values
EVs battery capacity	40 KWh
EVs battery Voltage	220 Volt
$(SC_{dual})j^{dis}$	20-80 %
SC_i^{EV}	0-100%
SC_{min}^{dual}	40%
SC_{max}^{dual}	70%
a	0.9
b	0.4
c	1
α	0.2
β	0.4
γ	0.5

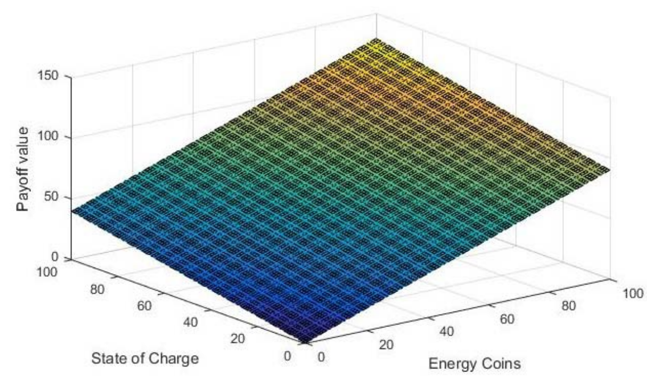

Fig. 3. Payoff value calculated for different state of charge and energy coins.

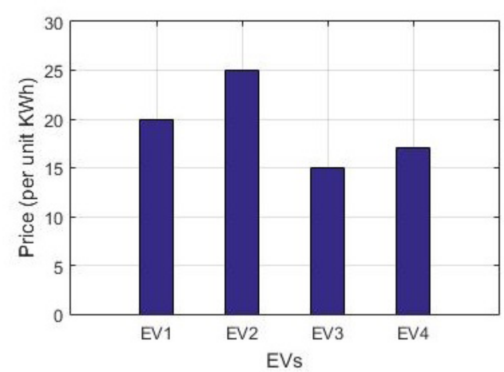

Fig. 4. Price incurred by dual-mode EVs for peak shaving.

Fig. 3 shows the payoff values with respect to the state of charge and energy coins required by the EVs to charge the battery. In this case, we have used the values of a and b is 0.9 and 0.4, respectively [54] as described in the Table II.

Similarly, in the peak shaving scenario, we have considered the case study having four dual-mode EVs, *i.e.,* EV1, EV2, EV3, and EV4 from the dataset available at [55]. The cost incurred by these EVs in the peak shaving process is shown in Fig. 4, and the number of EVs utilized that required energy from the dual-mode EVs is shown in Fig. 5. Moreover, the power exchanged between the dual-mode EVs and the energy

Authorized licensed use limited to: CITY UNIV OF HONG KONG. Downloaded on April 15,2023 at 09:13:53 UTC from IEEE Xplore. Restrictions apply.

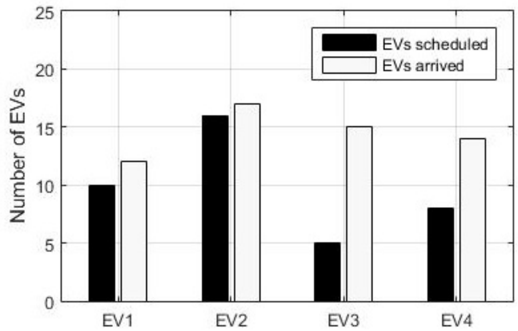

Fig. 5. Number of EVs required.

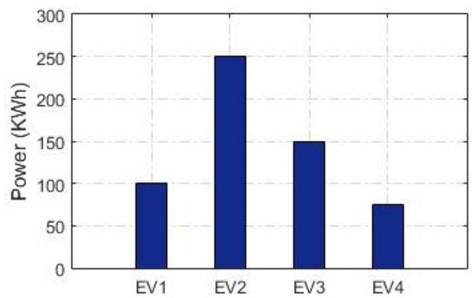

Fig. 6. Power discharged using dual-mode EVs.

TABLE III
DATA REPRESENTATION OF DUAL-MODE EVS

Type	Price (per unit KWh)	Power (KW)	EVs scheduled
EV1	20	100	10
EV2	25	250	16
EV3	15	150	5
EV4	17	75	8

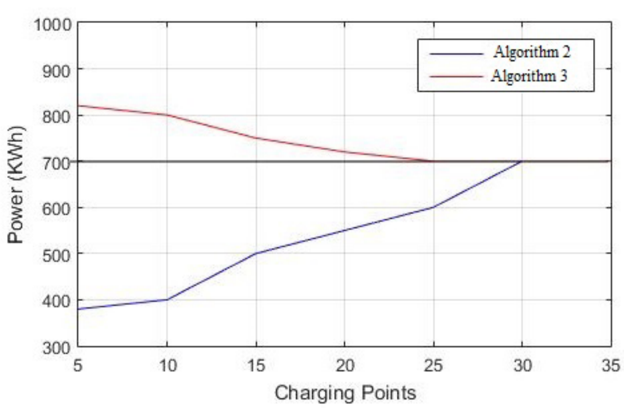

Fig. 7. Power variation with increasing number of charging points.

required EVs during energy transactions is shown in Fig. 6. The tabular representation of dual-mode EVs' data is as shown in Table III.

In this direction, Fig. 7 shows the power dissipated with respect to the charging points, *i.e.,* CSs and dual-mode EVs

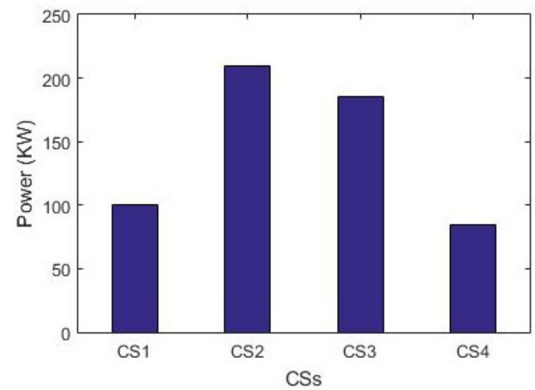

Fig. 8. Power discharged using CSs.

TABLE IV
DATA REPRESENTATION OF CSS

Type	Power (KW)	Battery Cycles	Measured SoC levels (%)
CS1	100	10, 50, 75, 100, 125	25, 45, 70, 50, 65, 40, 50
CS2	210	10, 50, 100, 200	90, 20, 50, 60, 40
CS3	185	100, 200	40, 55
CS4	85	50	45

charging points to charge the battery of EVs for energy management and peak load control scenarios. The load tends to get flattened with the increasing number of charging points. Moreover, the power exchanged between the CSs and the energy required EVs during energy transactions is shown in Fig. 8. The tabular representation of CSs data is as shown in Table IV.

With this, we have observed the price, energy, and cost factors of an EV in both cases EV. For EV1 in first energy management scenario, when EV acts as an energy consumer, the seller's price charged for an EV is shown in Fig. 9(a). The energy sold to that EV is shown in Fig. 9(b), and the cost were obtained from an EV in return to buy the energy is shown in Fig. 9(c). Similarly, the results were obtained for EV1, when EV acted as an energy supplier in a peak shaving scenario. The price charged by an EV to sell the energy is dissipated as shown in Fig. 10(a), and the observed sold energy is as shown in Fig. 10(b). In return for energy trading, an EV gets a profit, shown in Fig. 10(c). The tabular representation of EV price, energy, and cost factors in both cases is shown in Tables V and VI.

B. Security Evaluation

The security evaluation of the proposed blockchain-based energy trading scheme in V2G networks has been presented in this section. We have presented the security metrics such as throughput, time, block preparation time, and PoW generation time concerning the number of nodes and transactions. For this, we have created blocks and added transactions

Authorized licensed use limited to: CITY UNIV OF HONG KONG. Downloaded on April 15,2023 at 09:13:53 UTC from IEEE Xplore. Restrictions apply.

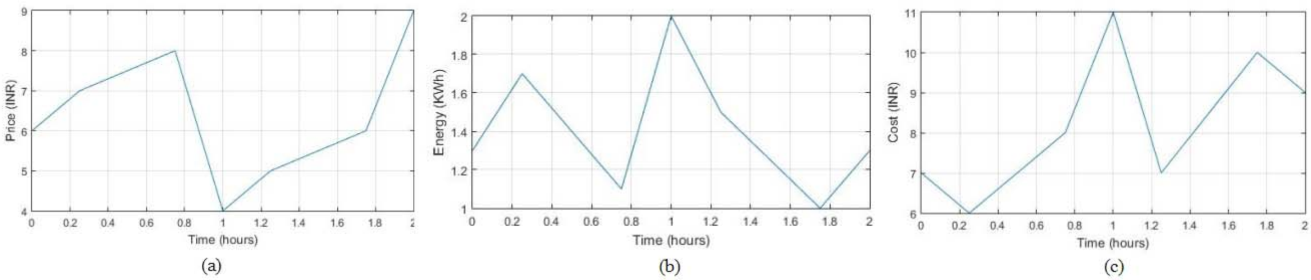

Fig. 9. (a) Price charged from EV per unit of energy (b) Energy sold to the EV (c) Cost incurred to the EV.

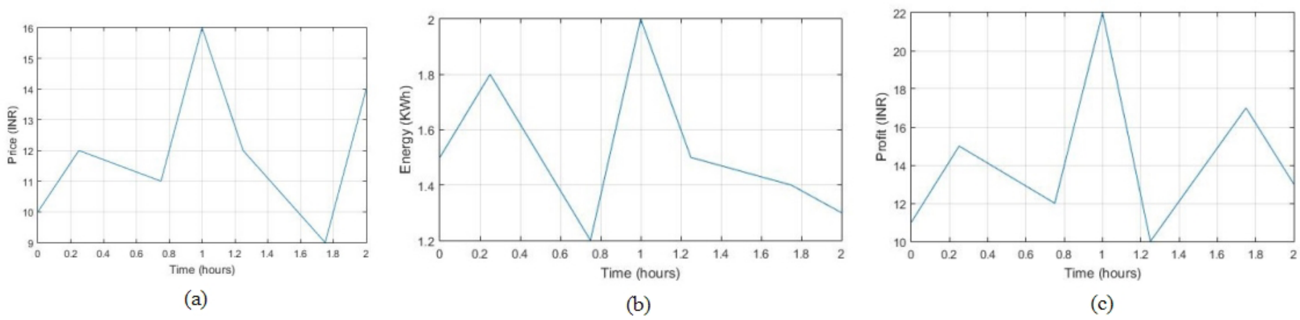

Fig. 10. (a) Price charged by EV per unit of energy (b) Energy sold by the EV (c) Profit earned by the EV.

TABLE V
PRICE, ENERGY, AND COST FACTORS OF EV'S ENERGY CONSUMER

Time (minutes)	**Price (INR)**	**Energy (tps)**	**Cost**
0	6	1.3	7
15	7	1.7	6
45	8	1.1	8
60	4	2	11
75	5	1.5	7
105	6	1	10
120	9	3	9

TABLE VI
PRICE, ENERGY, AND COST FACTORS OF EV'S ENERGY SUPPLIER

Time (minutes)	**Price (INR)**	**Energy (tps)**	**Cost**
0	10	1.5	11
15	12	1.8	15
45	11	1.2	12
60	11	2	22
75	12	1.5	10
105	9	1	17
120	14	1.2	13

on the Scientific Python Development Environment, Spyder [56], [57]. Fig. 11 shows the variation in throughput in transactions per second with an increase in the number of nodes. Similarly, Fig. 12 shows the computation time in comparison to the number of nodes. This figure clearly shows the steep increase in the initial stage, which further slows down approximately ten nodes. In another work, the block preparation time concerning an increase in the number of transactions is shown in Fig. 13, which is in linear form. Similarly, the Fig. 14 shows the PoW generation

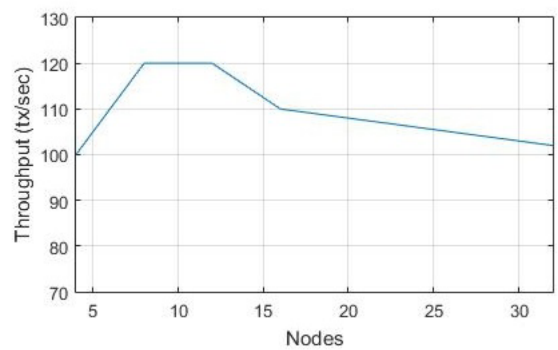

Fig. 11. Throughput vs. number of nodes.

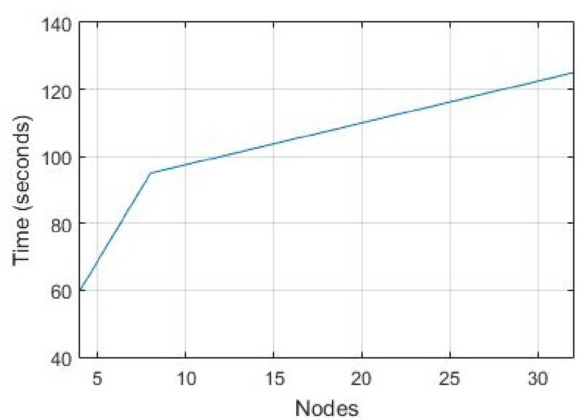

Fig. 12. Computation time vs. number of nodes.

time compared to an increase in the number of transactions. The tabular representation of security evaluation of the

Authorized licensed use limited to: CITY UNIV OF HONG KONG. Downloaded on April 15,2023 at 09:13:53 UTC from IEEE Xplore. Restrictions apply.

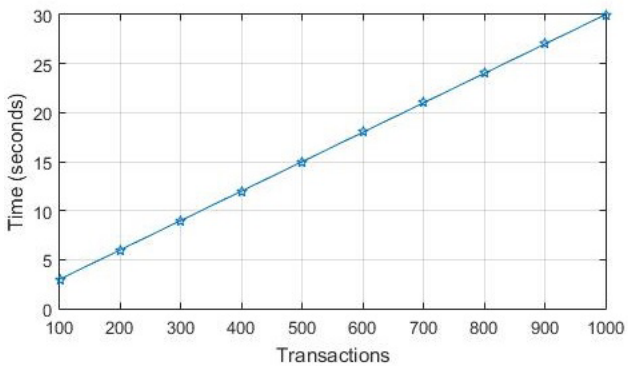

Fig. 13. Block generation time vs. number of transactions.

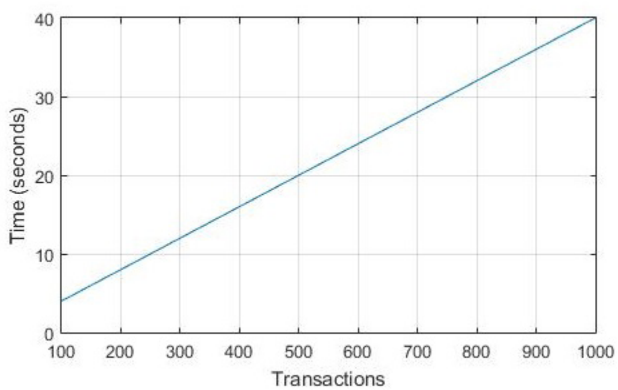

Fig. 14. PoW generation time vs. number of transactions.

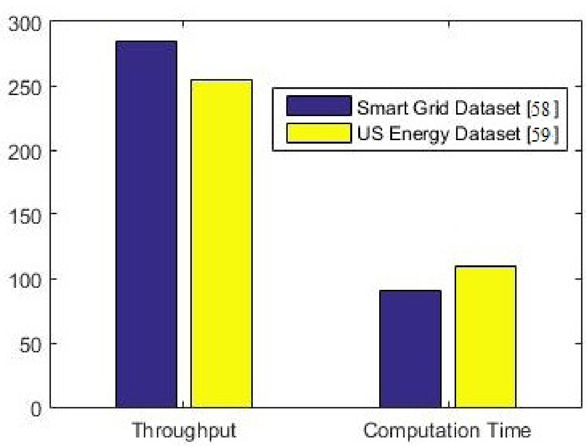

Fig. 15. Throughput and computation time for two datasets.

proposed blockchain-based energy trading scheme is shown in Table VII and VIII.

Finally, the proposed scheme has been evaluated concerning the transactions generated using two defined data sets, *i.e.,* smart grid lab [58], and US open energy information [59]. Fig. 15 depicts a higher throughput for US open energy information dataset. Similarly, it shows the lower computation time for open energy information dataset. This is because the concerned dataset is structured compared to the random data generated in the smart grid lab.

TABLE VII
DATA REPRESENTATION OF THROUGHPUT AND COMPUTATION TIME

Nodes	Throughput (tps)	Computation Time
4	100	60
8	120	95
12	120	100
16	110	105
20	118	110
24	106	115
28	104	120
32	102	125

TABLE VIII
DATA REPRESENTATION OF BLOCK GENERATION TIME AND POW GENERATION TIME

Transactions	Block Generation Time	PoW Generation Time
100	3	4
200	6	8
300	9	12
400	12	16
500	15	20
600	18	24
700	21	28
800	24	32
900	27	36
1000	30	40

VI. CONCLUSION

EVs are an alternative to fuel cars and gaining popularity because of reduced dependency on petrol and no harmful emissions that pollute the environment. EVs, when connected to the grid, act as either source or load according to the requirement. This paper has presented a blockchain-based energy trading scheme between the EVs and the CSs in a green V2G environment. The proposed scheme selects the miner nodes from the entities responsible for validating the energy trading transaction between them. We employ a game theory in energy trading that supports energy management and peak load control scenarios during off-peak and peak conditions, respectively, in a V2G environment. EVs have charged and discharging capabilities that reduce carbon emissions, a growing concern for a green V2G environment. The proposed scheme has been tested for various parameters, and its performance was found satisfactory. In future work, We will consider edge computing, where computational resources are distributed across network edges. As compared to centralized cloud computing, edge computing is more suitable to handle large-scale decentralized energy-trading transactions. Since the computational tasks are processed near end-users, dispensable network hops and transmission latency can be effectively eliminated.

ACKNOWLEDGMENT

The authors gratefully acknowledge technical and financial support from the Ministry of Education and King Abdulaziz University, DSR, Jeddah, Saudi Arabia.

Authorized licensed use limited to: CITY UNIV OF HONG KONG. Downloaded on April 15,2023 at 09:13:53 UTC from IEEE Xplore. Restrictions apply.

REFERENCES

[1] S. Esther, S. K. Singh, A. K. Goswami, and N. Sinha, "Recent challenges in vehicle to grid integrated renewable energy system: A review," in *Proc. 2nd Int. Conf. Intell. Comput. Control Syst. (ICICCS)*, Jun. 2018, pp. 427–435.

[2] B. Heile, "Smart grids for green communications [industry perspectives]," *IEEE Wireless Commun.*, vol. 17, no. 3, pp. 4–6, Jun. 2010.

[3] S. Mehar, S. Zeadally, G. Rémy, and S. M. Senouci, "Sustainable transportation management system for a fleet of electric vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 3, pp. 1401–1414, Jun. 2015.

[4] S. Habib, M. M. Khan, F. Abbas, L. Sang, M. U. Shahid, and H. Tang, "A comprehensive study of implemented international standards, technical challenges, impacts and prospects for electric vehicles," *IEEE Access*, vol. 6, pp. 13866–13890, 2018.

[5] M. Longo, W. Yaici, and F. Foiadelli, "Future developments in vehicle-to-grid technologies," in *Solving Urban Infrastructure Problems Using Smart City Technologies*. Amsterdam, The Netherlands: Elsevier, 2021, pp. 613–629.

[6] A. Šare, G. Krajačić, T. Pukšec, and N. Duić, "The integration of renewable energy sources and electric vehicles into the power system of the Dubrovnik region," *Energy, Sustainability Soc.*, vol. 5, no. 1, pp. 1–16, Dec. 2015.

[7] G. Wenzel, M. Negrete-Pincetic, and D. Olivares, "Real-time charging strategies for an electric vehicle aggregator to provide ancillary," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 1–11, Mar. 2017.

[8] R. S. Bali and N. Kumar, "Secure clustering for efficient data dissemination in vehicular cyber–physical systems," *Future Generat. Comput. Syst.*, vol. 56, pp. 476–492, Mar. 2016.

[9] E. Sortomme and M. A. El-Sharkawi, "Optimal charging strategies for unidirectional vehicle-to-grid," *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 131–138, Mar. 2011.

[10] B. Bibak and H. Tekiner-Moğulkoç, "A comprehensive analysis of vehicle to grid (V2G) systems and scholarly literature on the application of such systems," *Renew. Energy Focus*, vol. 36, pp. 1–20, Mar. 2021.

[11] X. Wang *et al.*, "Future communications and energy management in the Internet of Vehicles: Toward intelligent energy-harvesting," *IEEE Wireless Commun.*, vol. 26, no. 6, pp. 87–93, Dec. 2019.

[12] K. Z. Ghafoor *et al.*, "Millimeter-wave communication for Internet of Vehicles: Status, challenges, and perspectives," *IEEE Internet Things J.*, vol. 7, no. 9, pp. 8525–8546, Sep. 2020.

[13] B. Li, M. C. Kisacikoglu, C. Liu, N. Singh, and M. Erol-Kantarci, "Big data analytics for electric vehicle integration in green smart cities," *IEEE Commun. Mag.*, vol. 55, no. 11, pp. 19–25, Nov. 2017.

[14] L. Cai, J. Pan, L. Zhao, and X. Shen, "Networked electric vehicles for green intelligent transportation," *IEEE Commun. Standards Mag.*, vol. 1, no. 2, pp. 77–83, Jul. 2017.

[15] O. Abedinia, M. Lu, and M. Bagheri, "An improved multicriteria optimization method for solving the electric vehicles planning issue in smart grids via green energy sources," *IEEE Access*, vol. 8, pp. 3465–3481, 2020.

[16] C.-C. Lin, D.-J. Deng, C.-C. Kuo, and Y.-L. Liang, "Optimal charging control of energy storage and electric vehicle of an individual in the Internet of Energy with energy trading," *IEEE Trans. Ind. Informat.*, vol. 14, no. 6, pp. 2570–2578, Jun. 2018.

[17] X. Hu, K. Wang, X. Liu, Y. Sun, P. Li, and S. Guo, "Energy management for EV charging in software-defined green vehicle-to-grid network," *IEEE Commun. Mag.*, vol. 56, no. 5, pp. 156–163, May 2018.

[18] Y. Sun, X. Hu, X. Liu, X. He, and K. Wang, "A software-defined green framework for hybrid EV-charging networks," *IEEE Commun. Mag.*, vol. 55, no. 11, pp. 62–69, Nov. 2017.

[19] G. Chen, J. Wu, W. Yang, A. K. Bashir, G. Li, and M. Hammoudeh, "Leveraging graph convolutional-LSTM for energy-efficient caching in blockchain-based green IoT," *IEEE Trans. Green Commun. Netw.*, vol. 5, no. 3, pp. 1154–1164, Sep. 2021.

[20] G. Raja, A. Ganapathisubramaniyan, S. Anbalagan, S. B. M. Baskaran, K. Raja, and A. K. Bashir, "Intelligent reward-based data offloading in next-generation vehicular networks," *IEEE Internet Things J.*, vol. 7, no. 5, pp. 3747–3758, May 2020.

[21] C. Z. El-Bayeh, K. Alzaareer, A.-M.-I. Aldaoudeyeh, B. Brahmi, and M. Zellagui, "Charging and discharging strategies of electric vehicles: A survey," *World Electr. Vehicle J.*, vol. 12, no. 1, p. 11, Jan. 2021.

[22] H. Cai, Q. Chen, Z. Guan, and J. Huang, "Day-ahead optimal charging/discharging scheduling for electric vehicles in microgrids," *Protection Control Mod. Power Syst.*, vol. 3, no. 9, pp. 1–15, Dec. 2018.

[23] R.-C. Leou, "Optimal charging/discharging control for electric vehicles considering power system constraints and operation costs," *IEEE Trans. Power Syst.*, vol. 31, no. 3, pp. 1854–1860, May 2016.

[24] X. Jiang, J. Wang, Y. Han, and Q. Zhao, "Coordination dispatch of electric vehicles charging/discharging and renewable energy resources power in microgrid," *Proc. Comput. Sci.*, vol. 107, pp. 157–163, Jan. 2017.

[25] E. Hadian, H. Akbari, M. Farzinfar, and S. Saeed, "Optimal allocation of electric vehicle charging stations with adopted smart charging/discharging schedule," *IEEE Access*, vol. 8, pp. 196908–196919, 2020.

[26] Y. He, B. Venkatesh, and L. Guan, "Optimal scheduling for charging and discharging of electric vehicles," *IEEE Trans. Smart Grid*, vol. 3, no. 3, pp. 1095–1105, Sep. 2012.

[27] K. An, K.-B. Song, and K. Hur, "Incorporating charging/discharging strategy of electric vehicles into security-constrained optimal power flow to support high renewable penetration," *Energies*, vol. 10, no. 5, p. 729, May 2017.

[28] A. Mehrabi and K. Kim, "Low-complexity charging/discharging scheduling for electric vehicles at home and common lots for smart households prosumers," *IEEE Trans. Consum. Electron.*, vol. 64, no. 3, pp. 348–355, Aug. 2018.

[29] D. Said and H. T. Mouftah, "A novel electric vehicles charging/discharging management protocol based on queuing model," *IEEE Trans. Intell. Vehicles*, vol. 5, no. 1, pp. 100–111, Mar. 2020.

[30] S. Aggarwal, N. Kumar, S. Tanwar, and M. Alazab, "A survey on energy trading in the smart grid: Taxonomy, research challenges and solutions," *IEEE Access*, vol. 9, pp. 116231–116253, 2021.

[31] S. Aggarwal and N. Kumar, "A consortium blockchain-based energy trading for demand response management in vehicle-to-grid," *IEEE Trans. Veh. Technol.*, vol. 70, no. 9, pp. 9480–9494, Sep. 2021.

[32] G. Rathee, R. Iqbal, O. Waqar, and A. K. Bashir, "On the design and implementation of a blockchain enabled e-voting application within IoT-oriented smart cities," *IEEE Access*, vol. 9, pp. 34165–34176, 2021.

[33] G. Singh, N. Kumar, and A. K. Verma, "ANTALG: An innovative ACO based routing algorithm for MANETs," *J. Netw. Comput. Appl.*, vol. 45, pp. 151–167, Oct. 2014.

[34] N. Kumar, R. Iqbal, S. Misra, and J. J. P. C. Rodrigues, "An intelligent approach for building a secure decentralized public key infrastructure in VANET," *J. Comput. Syst. Sci.*, vol. 81, no. 6, pp. 1042–1058, 2015.

[35] S. Aggarwal, N. Kumar, and S. Tanwar, "Blockchain-envisioned UAV communication using 6G networks: Open issues, use cases, and future directions," *IEEE Internet Things J.*, vol. 8, no. 7, pp. 5416–5441, Apr. 2021.

[36] R. Jin, X. Zhang, Z. Wang, W. Sun, X. Yang, and Z. Shi, "Blockchain-enabled charging right trading among EV charging stations," *Energies*, vol. 12, no. 20, p. 3922, Oct. 2019.

[37] M. Kim *et al.*, "A secure charging system for electric vehicles based on blockchain," *Sensors*, vol. 19, no. 13, p. 3028, Jul. 2019.

[38] Q. Yang, H. Wang, T. Wang, S. Zhang, X. Wu, and H. Wang, "Blockchain-based decentralized energy management platform for residential distributed energy resources in a virtual power plant," *Appl. Energy*, vol. 294, Jul. 2021, Art. no. 117026.

[39] Z. Su, Y. Wang, Q. Xu, M. Fei, Y.-C. Tian, and N. Zhang, "A secure charging scheme for electric vehicles with smart communities in energy blockchain," *IEEE Internet Things J.*, vol. 6, no. 3, pp. 4601–4613, Jun. 2019.

[40] O. Samuel *et al.*, "Electric vehicles privacy preserving using blockchain in smart community," in *Proc. Int. Conf. Broadband Wireless Comput., Commun. Appl.* Antwerp, Belgium: Springer, 2019, pp. 67–80.

[41] F. Gao, L. Zhu, M. Shen, K. Sharif, Z. Wan, and K. Ren, "A blockchain-based privacy-preserving payment mechanism for vehicle-to-grid networks," *IEEE Netw.*, vol. 32, no. 6, pp. 184–192, Nov./Dec. 2018.

[42] E. M. Radi, N. Lasla, S. Bakiras, and M. Mahmoud, "Privacy-preserving electric vehicle charging for peer-to-peer energy trading ecosystems," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2019, pp. 1–6.

[43] Y. Li and B. Hu, "A consortium blockchain-enabled secure and privacy-preserving optimized charging and discharging trading scheme for electric vehicles," *IEEE Trans. Ind. Informat.*, vol. 17, no. 3, pp. 1968–1977, Mar. 2021.

[44] Y. Li and B. Hu, "An iterative two-layer optimization charging and discharging trading scheme for electric vehicle using consortium blockchain," *IEEE Trans. Smart Grid*, vol. 11, no. 3, pp. 2627–2637, May 2020.

[45] C. Liu, K. K. Chai, X. Zhang, E. T. Lau, and Y. Chen, "Adaptive blockchain-based electric vehicle participation scheme in smart grid platform," *IEEE Access*, vol. 6, pp. 25657–25665, 2018.

Authorized licensed use limited to: CITY UNIV OF HONG KONG. Downloaded on April 15,2023 at 09:13:53 UTC from IEEE Xplore. Restrictions apply.

[46] A. Yildizbasi, "Blockchain and renewable energy: Integration challenges in circular economy era," *Renew. Energy*, vol. 176, pp. 183–197, Oct. 2021.

[47] Y. Xu, Z. Liu, C. Zhang, J. Ren, Y. Zhang, and X. Shen, "Blockchain-based trustworthy energy dispatching approach for high renewable energy penetrated power systems," *IEEE Internet Things J.*, early access, Oct. 6, 2021, doi: 10.1109/JIOT.2021.3117924.

[48] A. Jindal, G. S. S. Aujla, N. Kumar, and M. Villari, "GUARDIAN: Blockchain-based secure demand response management in smart grid system," *IEEE Trans. Services Comput.*, vol. 13, no. 4, pp. 613–624, Jul./Aug. 2020.

[49] N. Kumar, S. Aggarwal, and P. Raj, *The Blockchain Technology for Secure and Smart Applications Across Industry Verticals*, vol. 121. New York, NY, USA: Academic, 2021.

[50] S. Aggarwal, R. Chaudhary, G. S. Aujla, N. Kumar, K.-K. R. Choo, and A. Y. Zomaya, "Blockchain for smart communities: Applications, challenges and opportunities," *J. Netw. Comput. Appl.*, vol. 144, pp. 13–48, Oct. 2019.

[51] J. Kang, R. Yu, X. Huang, S. Maharjan, Y. Zhang, and E. Hossain, "Enabling localized peer-to-peer electricity trading among plug-in hybrid electric vehicles using consortium blockchains," *IEEE Trans. Ind. Informat.*, vol. 13, no. 6, pp. 3154–3164, Dec. 2017.

[52] A. Gervais, G. O. Karame, K. Wüst, V. Glykantzis, H. Ritzdorf, and S. Capkun, "On the security and performance of proof of work blockchains," in *Proc. ACM SIGSAC Conf. Comput. Commun. Secur.*, Oct. 2016, pp. 3–16.

[53] M. J. Osborne and A. Rubinstein, *A Course Game Theory*. Cambridge, MA, USA, MIT Press, 1994.

[54] K. Kaur, A. Dua, A. Jindal, N. Kumar, M. Singh, and A. Vinel, "A novel resource reservation scheme for mobile PHEVs in V2G environment using game theoretical approach," *IEEE Trans. Veh. Technol.*, vol. 64, no. 12, pp. 5653–5666, Dec. 2015.

[55] IEEE Power and Energy Society. *Database With a 24-Period Scenario of 1800 Realistic EVS*. Accessed: Feb. 14, 2021. [Online]. Available: https://site.ieee.org/pes-iss/data-sets/elec/

[56] Spyder. *Python Development Environment*. Accessed: Sep. 26, 2021. [Online]. Available: https://www.spyder-ide.org/

[57] Customer-Led Network Revolution. *Enhanced Profiling of Domestic Customers With Electric Vehicles (EVS)*. Accessed: Feb. 14, 2021. [Online]. Available: http://www.networkrevolution.co.U.K./project-library/dataset-tc6-enhanced-profiling-electric-vehicles-ev-users-flat-rate-tariff/

[58] D. Kaur, G. S. Aujla, N. Kumar, A. Y. Zomaya, C. Perera, and R. Ranjan, "Tensor-based big data management scheme for dimensionality reduction problem in smart grid systems: SDN perspective," *IEEE Trans. Knowl. Data Eng.*, vol. 30, no. 10, pp. 1985–1998, Feb. 2018.

[59] Open Energy Information. *Commercial and Residential Hourly Loadprofiles for All TMY3 Locations in Theunited States*. Accessed: Jul. 15, 2021. [Online]. Available: https://data.openei.org/

Ahmed Barnawi received the M.Sc. degree from UMIST, U.K., in 2001, and the Ph.D. degree from the University of Bradford, U.K., in 2005. He is currently a Professor with the Faculty of Computing and IT, King Abdulaziz University, where he is also the Managing Director of the KAU Cloud Computing and Big Data Research Group. He has published more than 100 articles in peer-reviewed journals. His research interests include big data, cloud computing, and advanced mobile robotic application.

Shubhani Aggarwal received the B.Tech. degree in computer science and engineering from Punjabi University, Patiala, India, in 2015, and the M.E. degree in computer science from Panjab University, Chandigarh, India, in 2017. She is currently pursuing the Ph.D. degree with the Thapar Institute of Engineering and Technology (Deemed to be University), Patiala. Some of her research findings are authored or coauthored in top-cited journals, such as the IEEE INTERNET OF THINGS, IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, IEEE TRANSACTIONS ON INDUSTRIAL INFORMATICS, *IEEE Network* magazine, *Journal of Network and Computer Applications* (Elsevier), *Computers & Security*, *Mobile Networks and Applications*, and *Computer Communications*. Her research interests include blockchain, cryptography, the Internet of Drones, and information security.

Neeraj Kumar (Senior Member, IEEE) is currently working as a Full Professor with the Department of Computer Science and Engineering, Thapar Institute of Engineering and Technology (Deemed to be University), Patiala, India. He is also an Adjunct Professor at Asia University, Taiwan; King Abdul Aziz University, Jeddah, Saudi Arabia; and Newcastle University, U.K. He has published more than 400 technical research papers (DBLP: https://dblp.org/pers/hd/k/Kumar_0001:Neeraj) in top-cited journals and conferences, which are cited more than 23500 times from well-known researchers across the globe with current H-index of 85 (Google scholar: https://scholar.google.com/citations?hl=en&user=gL9gR-4AAAAJ). He has guided many research scholars leading to Ph.D. and M.E./M.Tech. His research was supported by the funding from various competitive agencies across the globe. His broad research areas are green computing and network management, the IoT, big data analytics, deep learning, and cyber-security. He has also edited/authored ten books with international/national publishers like IET, Springer, Elsevier, and CRC, such as *Security and Privacy of Electronic Healthcare Records: Concepts, Paradigms and Solutions*, *Machine Learning in Cognitive IoT* (CRC Press), *Blockchain, Big Data and Machine Learning* (CRC Press), *Blockchain Technologies Across Industrial Vertical* (Elsevier), *Multimedia Big Data Computing for IoT Applications: Concepts, Paradigms and Solutions*, *Proceedings of First International Conference on Computing, Communications, and Cyber-Security* (IC4S 2019), and *Probabilistic Data Structures for Blockchain-Based Internet of Things Applications* (CRC Press). One of the edited text-book titled "*Multimedia Big Data Computing for IoT Applications: Concepts, Paradigms and Solutions*" published by Springer in 2019 is having 3.5 million downloads till June 2020. It attracts attention of the researchers across the globe (https://www.springer.com/in/book/9789811387586). He is a highly-cited researcher from WoS from 2019 to 2021.

Prof. Kumar has organized various special issues of journals of repute from IEEE, Elsevier, and Springer. He has been the Workshop Chair at IEEE GLOBECOM 2018, IEEE INFOCOM 2020, and IEEE ICC 2020, and the track chair. He is serving as an Editor of *ACM Computing Surveys*, IEEE TRANSACTIONS ON SUSTAINABLE COMPUTING, IEEE TRANSACTIONS ON NETWORK AND SERVICE MANAGEMENT, *IEEE Network* magazine, *IEEE Communications Magazine*, *Journal of Networks and Computer Applications* (Elsevier), *Computer Communications* (Elsevier), and *International Journal of Communication Systems* (Wiley).

Daniyal M. Alghazzawi (Senior Member, IEEE) received the M.Sc. degree in teaching and leadership and the M.Sc. and Ph.D. degrees in computer science from The University of Kansas, USA, in 2004 and 2007, respectively. In 2007, he has served as the Head of Department for five years, and then, he has also served as the Vice Dean of the Development of the Deanship of Information Technology for two years. In 2010, he became an Honorary Lecturer with the School of Computer Science and Electronic Engineering, University of Essex, U.K. He is currently a Professor with the Computing Information Systems Department and the Head of the Information Security Group, King Abdulaziz University.

Bander Alzahrani (Member, IEEE) received the M.Sc. degree in computer security and the Ph.D. degree in computer science from the University of Essex, U.K., in 2010 and 2015, respectively. He is currently an Associate Professor with the Faculty of Computing and Information Technology, King Abdulaziz University, Saudi Arabia. He has led more than ten national research projects and coauthored more than 45 research articles in peer-reviewed journals and conferences. His current research interests include WSN, ICN, and secure content routing.

Mehrez Boulares received the master's degree from the Higher National Engineering School of Tunis in 2009 and the Ph.D. degree from the University of Sfax, Tunisia, in December 2016. He is currently a Post-Doctoral Researcher in information and communication technologies with the Faculty of Computing and IT (FCIT), King Abdulaziz University (KAU). He is also an active researcher in the artificial intelligence field. He published over 14 articles in peer-reviewed journals and international conferences.

Authorized licensed use limited to: CITY UNIV OF HONG KONG. Downloaded on April 15,2023 at 09:13:53 UTC from IEEE Xplore. Restrictions apply.