A Blockchain-Based Framework for Lightweight Data Sharing and Energy Trading in V2G Network

Vikas Hassija, Vinay Chamola, Sahil Garg, *Member, IEEE*, Dara Nanda Gopala Krishna, Georges Kaddoum, *Member, IEEE*, and Dushantha Nalin K. Jayakody, *Senior Member, IEEE*

***Abstract*—The Vehicle-to-Grid (V2G) network is, where the battery-powered vehicles provide energy to the power grid, is highly emerging. A robust, scalable, and cost-optimal mechanism that can support the increasing number of transactions in a V2G network is required. Existing studies use traditional blockchain as to achieve this requirement. Blockchain-enabled V2G networks require a high computation power and are not suitable for micro-transactions due to the mining reward being higher than the transaction value itself. Moreover, the transaction throughput in the generic blockchain is too low to support the increasing number of frequent transactions in V2G networks. To address these challenges, in this paper, a lightweight blockchain-based protocol called Directed Acyclic Graph-based V2G network (DV2G) is proposed. Here blockchain refers to any Distributed Ledger Technology (DLT) and not just the bitcoin chain of blocks. A tangle data structure is used to record the transactions in the network in a secure and scalable manner. A game theory model is used to perform negotiation between the grid and vehicles at an optimized cost. The proposed model does not require the heavy computation associated to the addition of the transactions to the data structure and does not require any fees to post the transaction. The proposed model is shown to be highly scalable and supports the micro-transactions required in V2G networks.**

***Index Terms*—Directed acyclic graph, vehicle-to-grid, energy trading, distributed applications, consensus, smart grid, blockchain.**

Manuscript received August 30, 2019; revised November 29, 2019; accepted December 29, 2019. Date of publication January 16, 2020; date of current version June 18, 2020. This work was supported in part by the Scheme for Promotion of Academic and Research Collaboration (SPARC), Ministry of Human Resource Development, India under the No. P14, in part by the framework of Competitiveness Enhancement Program of the National Research Tomsk Polytechnic University, Russia, and in part by the International Cooperation Project of Sri Lanka Technological Campus, Sri Lanka and Tomsk Polytechnic University under Grant RRSG/19/5008. The review of this article was coordinated by Prof. H. Li. *(Corresponding author: Sahil Garg.)*

V. Hassija and D. N. G. Krishna are with the Department of CSE and IT, Jaypee Institute of Information Technology, Noida 201304, India (e-mail: vikas.hassija@jiit.ac.in; nandudara3105@gmail.com).

V. Chamola is with the Department of Electrical and Electronics Engineering, Birla Institute of Technology and Science-Pilani, Pilani Campus 333031, India (e-mail: vinay.chamola@pilani.bits-pilani.ac.in).

S. Garg and G. Kaddoum are with the Electrical Engineering Department, École de technologie supérieure, Université du Québec, Montréal, QC H3C 1K3, Canada (e-mail: sahil.garg@ieee.org; georges.kaddoum@etsmtl.ca).

D. N. K. Jayakody is with the School of Computer Science and Robotics, National Research Tomsk Polytechnic University, Tomsk 634050, Russia, and also with the Centre for Telecommunication Research, Faculty of Engineering, Sri Lanka Technological Campus, Padukka 10500, Sri Lanka (e-mail: nalin.jayakody@ieee.org).

Digital Object Identifier 10.1109/TVT.2020.2967052

I. Introduction

DUE TO a lack of non-renewable energy resources, revolutionary changes are taking place in the energy sector in order to generate renewable energy. Huge developments have been recently witnessed in Renewable Energy Resources (RES), such as wind and solar photovoltaic panels. The issue with RES is that their power generation fluctuates as per the weather and climate conditions, and the exact prediction of the amount of generated energy is not easy. Thus, traditional power generators face unpredictable fluctuations in their power demand due to the uncertainty in RES. The smart grid is anticipated as a next-gen power grid that can help distribution companies provide local resources to their customers, to overcome this problem. With smart grids, information can be exchanged between consumers and the grid, and energy flow can take place between consumers and different parts of the smart grid. In this context, Electric Storage Units (ESUs) [1] are enabled using smart grids that store excess energy, available at customers. Local neighborhood demands and other internal demands for energy can be met using these storage units. The smart grid makes the interaction between power sources that are situated in different places possible. Since many consumers are capable of generating energy, trading the excess amount of energy with other consumers seems plausible. For example, neighbor A can sell the surplus of clean, renewable energy generated from the solar panel on his/her rooftop to neighbor B.

To meet the energy demand and to efficiently use the generated renewable energy, it is important to generate possibilities of energy trading among all consumers and producers. Without such a model, some consumers will continue to face energy deficiency, and some producers will have to waste the extra generated energy without any monetary benefits. The concept of Vehicle-to-Grid (V2G) was recently introduced to solve these problems [2]. Also, the Electric Vehicle (EV) [3] is emerging in the energy market, which aims to ease the load imposed on the traditional grid by applying such as Grid-to-Vehicle (G2V) and V2G. Here, V2G is defined as the provision of energy and other necessary support from an EV to the electric grid. Meanwhile, V2G can be seen as one step ahead of smart charging. In V2G networks, EVs use bi-directional charging and can sell/buy energy to/from the grid depending on the situations [4], [5]. A V2G technological scheme was introduced in Lombok and Utrecht to illustrate the opportunities that EVs provide.

V2G is a suitable solution for better resource utilization and revenue maximization, since vehicles remain parked for an

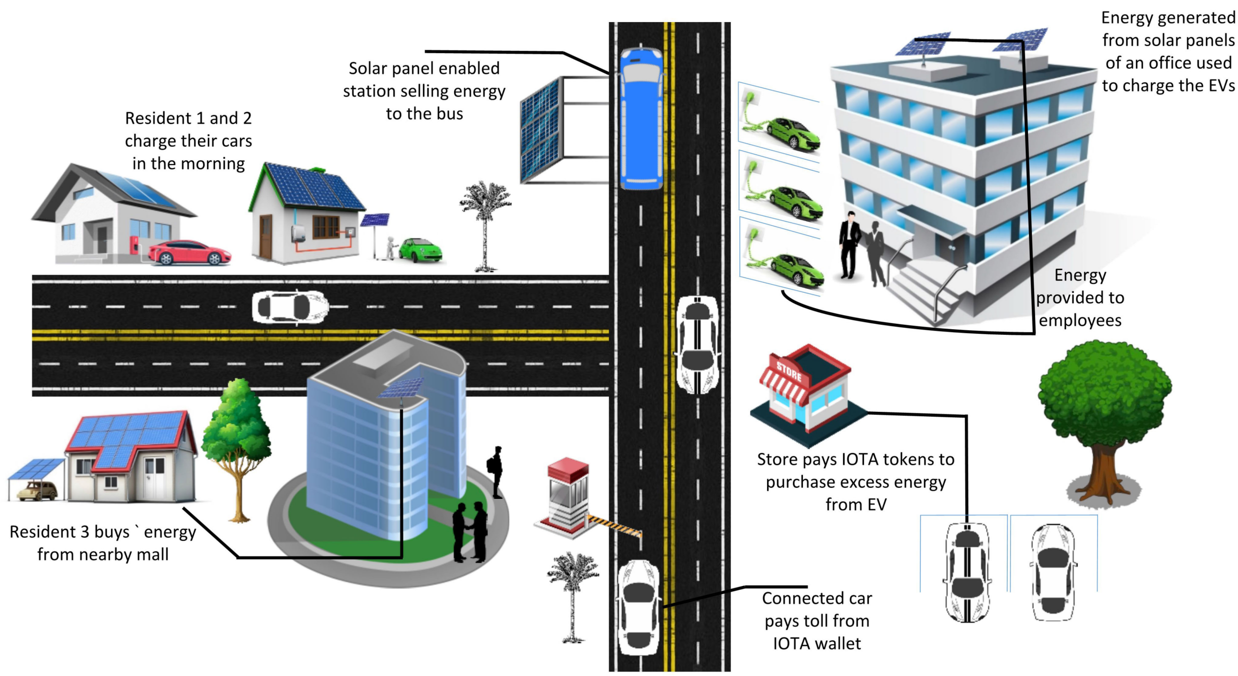


Fig. 1. Smart city scenario.

TABLE I
RELATED WORK ON VEHICLE TO GRID COMMUNICATION

Year	Author	Contributions
2016	Rongqing Zhang *et al.* [23]	A three-party architecture to achieve effective RES in power system.
2016	Suli Zou *et al.* [24]	Auction based game theoretic approaches for bargaining energy trading prices between EVs and market.
2017	Zhaoxi Liu *et al.* [25]	Non-cooperative nash equilibrium game scheduling techniques for charging and discharging of EV.
2017	Jiawen Kang *et al.* [26]	Method of consortium blockchain that uses P2P energy trading model for EVs.
2017	Se-Chang Oh *et al.* [27]	Blockchain-based energy trading system showing exchange transaction between users .
2018	Esther Mengelkamp *et al.* [28]	Advantages and disadvantages of using blockchain for trading energy.
2019	Merlinda Andoni *et al.* [29]	Key features of DLT needed for trading energy in P2P network.
2019	Sahil Garg *et al.* [30]	Hierarchical authentication mechanism based on blockchain for trading energy in V2G network.

average time of 96% throughout the life of the vehicle [6]. EV can interact and trade energy with other traders, and it can also work independently by participating in energy trading with the grid based on its battery status [7]. The only condition imposed here is that the vehicles and the other traders and grid should be within the same network. Many smart, sustainable, and green solutions have been developed in the last decade, to consume the energy produced in an environmentally sustained way [8]. For example, residential areas are deployed with Distributed Energy Resources (DERs) [9]. To manage the electricity in the grid effectively, various demand response energy management services were established in [10]. Figure. 1 shows a pictorial representation of the scenario under consideration.

The traditional method of storing every single energy transaction on central servers is not feasible for such micro-transactions. Using cryptocurrency is a promising alternative for registering each energy or data transaction. Distributed Ledger Technology (DLT) plays a major role in storing these cryptocurrency-based transactions. For storing all transaction data in a distributed storage, the concept of blockchain is widely explored in the energy market [11]. Blockchain allows a secure Peer-to-Peer (P2P) transaction platform. In the P2P platform, no utility company acts as an intermediary and any individual node in the network can act as a buyer or a seller. In such a scenario, households can be consumers, as well as prosumers, i.e., entities that can produce and consume their electricity themselves and can also sell excess electricity [12]. Recently many researchers have focused their work towards using blockchain-based ledger technology for creating a P2P platform for energy trading [13], [14]. Such a transition is due to the following major advantages of blockchain, or any DLT, over traditional centralized systems.

1) Blockchain provides decentralized and distributed ledger for the storage and processing data, there is no payment to any central authority required to get data storage and organizing facilities [15].
2) There is no need to trust any third party because the state of the chain is decided by the majority of participants agreeing on the smart contract.
3) Records of transactions are tamper-resistant and accountable.
4) Self-executing lines of code can be added as a smart contract to prevent all kinds of disputes among the involved parties.
5) The complete control of the asset movement is with the smart contract and transactions can be immediately processed using cryptocurrencies.

However, the generic blockchain algorithm suffers from some fundamental drawbacks such as the latency of transaction confirmation, the scalability limitations, and the probabilistic nature of consensus algorithms [16], [17]. Microtransactions cannot be added in normal blockchains as the incentive given to the miners for such transactions ends up to be higher than the actual transaction value. Processing fees of transactions are increasingly high and the size of the block is constrained due to which implies that a large number of transactions can't be handled, making traditional blockchain less practical [18]. Various works propose the use of other consensus algorithms such as Proof of Stake (POS), Proof of Burn (POB), or Proof of Elapsed Time (POET) to overcome the limitations of the generic blockchain. However, all these consensus algorithms follow the Proof of Work (POW) algorithm. The network development and the distribution of currency depend on the POW algorithm only [19], and the other algorithms can be applied only after using POW for a considerable time. A new distributed application cannot be created using the POS consensus process as none of the nodes in the network has any stake or cryptocurrency to burn. Therefore, in this paper Directed Acyclic Graph (DAG) based IOTA ledger is used to perform P2P transactions in V2G energy trading [20]. Unlike normal blockchain, IOTA-based blockchain ledger does not have any miners to process transactions [21]. However, the facilities provided by the normal blockchain, such as distributed and transparent transaction records, are fulfilled by IOTA-based blockchain [22]. Moreover, the IOTA network is not susceptible to distributed denial of service attacks as no single node is given any unique privilege to create or maintain the data structure. Therefore, IOTA-based blockchain is the right option for trading energy in a P2P domain in the V2G network.

A. Research Contributions of This Work

We summarize the main contributions of this work as follows:

1) We propose a unique and secure energy trading platform in V2G network.
2) It is based on Directed Acyclic Graph (DAG) which uses tangle data structure to store transactions.
3) We implement the tip selection algorithm which allows buyers and sellers to add new transactions in tangle without needing any miners.
4) The proposed energy trading model uses game theory for selecting sellers and price at which sellers will trade energy with buyers.
5) The use of game theory ensures nash equilibrium among buyers and sellers thereby maintaining the energy selling price.

B. Organization

The current state and recent works related to energy trading in V2G networks using traditional and blockchain systems are presented in Section II. Some background information and key characteristics of the IOTA ledger technology and system model for P2P energy trading in the V2G network are presented in Section III. Section IV presents the game theory strategy for selecting the right seller and buyer. While the auctioning model to bargain the energy price is discussed in Section V. The Ascending-Price progressive auction algorithms are presented in Section V. In Section VI, the simulation results are presented and are compared with the existing traditional models for V2G energy trading. The conclusion of the paper is presented in Section VII.

II. Related Work

Many researchers are working on the idea of trading energy from V2G using EV and smart grid. A three-party architecture was proposed to achieve effective RES in the power system using EVs, smart grid, and ESUs in [23]. The architecture involves a flexible and complex exchange between EVs and the smart grid, where a framework is proposed to manage energy effectively and intelligently in a power system. In [31], a response scheduling algorithm to accommodate more EVs was introduced. In this work, a framework to regulate the performance of the V2G network in an efficient manner were proposed. According to their dispatch algorithm for EVs, remote signals are used for switching charging stations on and off.

Authors of [25], w5 devised a non-cooperative nash game scheduling techniques for discharging and charging of EV. The problem of overload of the grid at peak hours due to the high demand of charge by EVs is considered. A centralized optimization problem aiming to minimize the squared Euclidean distance between the instantaneous energy demand and the average demand of buildings by controlling the charging and discharging schedules of Plug- in Hybrid Electric Vehicles (PHEVs) is formulated. Meanwhile, the authors of [25] proposed an aggregative game model that helps in the scheduling of EVs optimal charging. Quadratic programming is used to calculate the nash equilibrium of the game model in an optimized way. Meanwhile, Woongsup Lee *et al.* [32] have analyzed price competition between the newly developed Electric Vehicle Charging Stations (EVCSs) and Renewable Power Generators (RPGs) using game theory.

Auction-based game-theoretic approaches have been introduced by the authors of [24], which can be used for bargaining the price of energy traded between EVs and market and solve the coordination problems arising from charging EVs. The convergence of the auction process to the nash equilibrium with the help of a numerical example was also demonstrated. The authors of [33] developed an auction mechanism that can determine the price for trading energy between EVs and smart grids. Simulation results show significant improvements in the average utility when compared with a greedy approach. In [34], authors proposed a Bayesian Coalition Negotiation Game (BCNG) and achieved a nash equilibrium for managing and trading energy in the V2G environments. A Secure Payoff Function (SPF) to avoid the misuse of consumed energy was proposed. Protection from attacks while distributing power and mutual authentication is also provided in the proposed scheme. Finally, the authors of [35] proposed charging and discharging cooperation of PHEVs in V2G networks using a game-theoretic approach in their research work. The significant reduction of peak-valley difference in the smart grid's electricity load was obtained in the simulation results.

All the above works more or less depend on centralized architectures. Such architectures suffer from some fundamental defects, such as a single point of failure, security issues, and scalability issues [36]. Few recent works have shown interest in creating a distributed P2P network for energy trading using traditional blockchain. Authors of [26] proposed a method of consortium blockchain which uses P2P energy trading among EVs. To illustrate the operations taking place in energy trading, they proposed a method known as P2P Electricity Trading System with Consortium Blockchain (PETCON). Along with the PETCON method, the issue of energy pricing and the amount of energy traded among EVs was solved using iterative double auction game theory. Andoni M. *et al.* [29] discussed the key features of DLTs needed for trading energy, with a focus on distributed consensus algorithms, taxonomies of blockchain architecture, and the suitability of those algorithms in smart grid-based networks. Along with that, the challenges that are going to come in the way of developing an energy trading platform for the V2G network were discussed.

For trading energy in the V2G environment, authors of [30] discussed a hierarchical authentication mechanism based on blockchain. In their work, they used elliptic curve cryptography (ECC) for hierarchical authentication. ECC can be used for preserving EVs' anonymity and for supporting mutual authentication among charging stations (CSs) and EVs. The protection against different attacks has been validated using the Automated Validation of Internet Security Protocols and Applications (AVISPA) tool. Esther Mengelkamp *et al.* [28] simulated the blockchain-based local energy market (LEM) and have discussed the advantages and disadvantages of using blockchain for energy trading. They implemented a closed double auction mechanism via a smart contract using blockchain. The authors of [27] implemented the blockchain-based energy trading system, showing the process by which a producer and consumer nodes complete their exchange transactions. The interaction between the producer and consumer nodes and implementation of an energy trading system is shown using Savoir (python-based JsonRPC module). Although the generic blockchain-based frameworks help provide a secure distributed environment for P2P energy transactions, such frameworks also have some in-built limitations. Normal blockchain frameworks cannot support micro-transactions between a large number of nodes. Also, the forking and pruning issues in generic blockchain result the efficiency of the framework. Therefore, in this work an IOTA based P2P distributed network that can support micro-transactions with a large number of nodes is proposed. The proposed model is free from forking and pruning issues, and no mining fees are involved while validating the transactions. In the next Section, the prelims of the IOTA network and the proposed network model are discussed.

III. Network Creation and Preliminaries

IOTA ledger turns out to be a feasible option, to record and process the large number of frequent micro-transactions in the V2G network. IOTA is a DAG-based distributed ledger, where a DAG is referred to as a tangle in IOTA [20]. IOTA tangle provides interesting features such as fee-less micro-transactions, asset transfer, and trusted identities. When all the devices get connected to the IOTA network, they act as nodes in the network. The devices can securely transfer data and perform transactions directly with each other without involving any centralized third party. The EVs, when parked, can buy energy from nearby malls or offices, or can use the extra energy to power the street lights nearby at night.

A. Digital Identity

One of the most important building blocks for any DLT is digital identity. Digital identity is used to ensure the level of trust among the parties involved in energy transactions. Recently, the IOTA community has developed a digital biometric identification in which a person's palm vein pattern is used to identify him/her, namely the IAMPASS biometric palm vein authentication for digital identity in IOTA [37]. Centralized and traditional identification methods often fail to secure user data that is growing at a tremendous rate. Therefore, verified digital identity, stored on a distributed ledger, is an innovative alternative. Also, digital identity verification methods are free from fee expenses charged by third-parties for providing authentication and verification services.

Each smart device has its own pseudo-anonymous, a virtual and private wallet that stores IOTA tokens used for making transactions. To use an IOTA network, the user has to create a secret password called seed (a string of 81 trytes) [38]. Each seed can create 9^{57} addresses and private keys. Users can send messages and tokens to other users using the address field in the transaction which is public. To withdraw IOTA tokens from addresses, bundles are signed using unique private keys.

B. Tip Selection Algorithm

In generic Blockchain, to verify whether the user is making an authentic transaction or not, computing power is a major factor. Miners are used to validate normal blockchain, where all transactions are to be added in the next block. The task of mining in the traditional blockchain is done by new transactions in IOTA, i.e., approval of transactions is done by the participation of all the nodes directly or indirectly present in the network, thereby making miners and participant nodes indistinct. This prevents the IOTA network from distributed denial of service (DDOS) attacks. Whenever a new transaction comes in the tangle, it has to select and approve two previous transactions. An edge is created between the selected transactions and the newly added transaction. The new transaction has to solve a cryptographic puzzle, to approve an existing transaction. Once this is done, the new transaction waits for its approval by another upcoming transaction. Unapproved transactions in a DAG are referred to as a tip. The tip-selection algorithm decides how the tip gets validated by new transactions [20]. Hence, the transaction confirmation latency depends on tip-selection algorithms and the rate at which new transactions are added in the tangle. The frequency of transactions that can get added in the IOTA network is very high compared to the ten minutes waiting time to add a new block in normal blockchain.

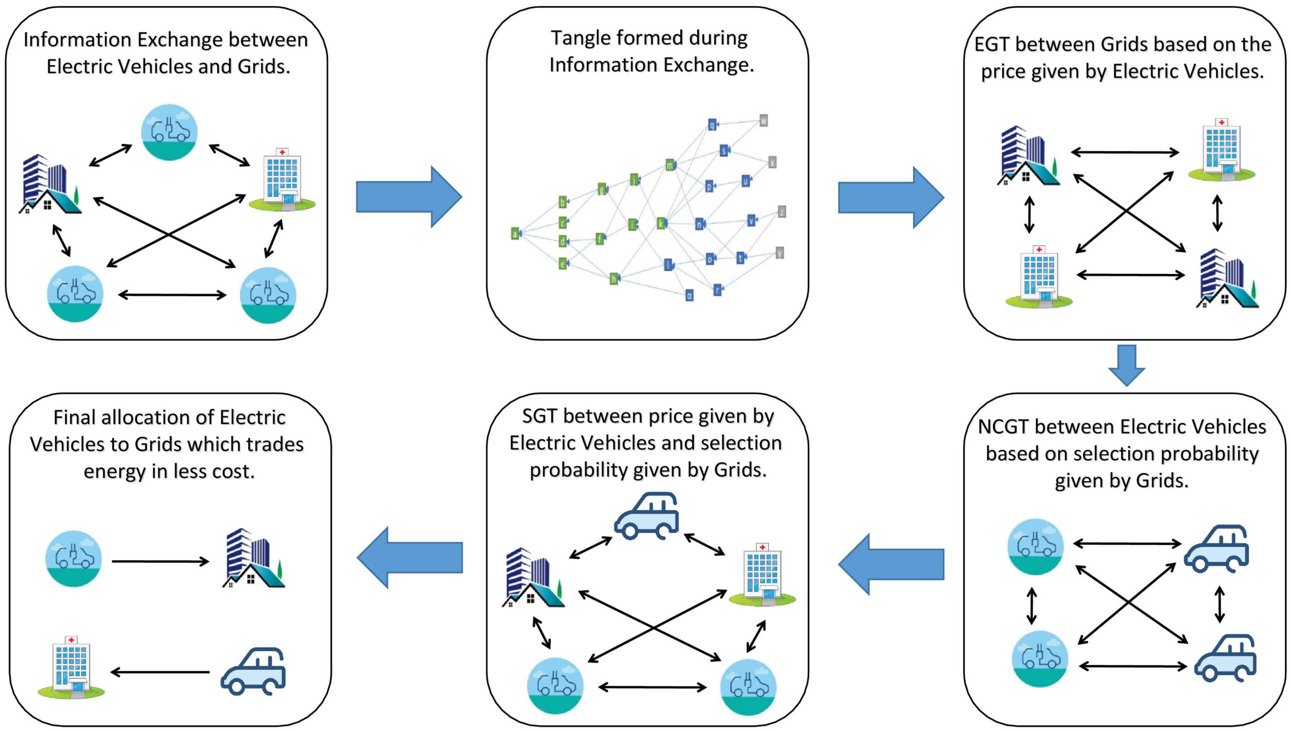


Fig. 2. Energy trading between electric vehicles and grids.

The tip selection algorithm gives a special rating to each transaction, which is equal to the number of transactions that reference it. The larger the weight of a transaction the more important it is. The aim of this implementation is to select two non-conflicting tips for the verification of the newly arrived transaction. The cumulative Weight (CW) of any transaction X is given as its own weight plus the weight of transactions that approved it directly or indirectly. For example if $X_2, X_3, X_4, \ldots, X_N$ are the transactions that approve X_1 directly or indirectly, and the weight of X_1 is W_{X1} and while the weight of $X_2, X_3, X_4, \ldots, X_N$ is $W_{X2,3,4,\ldots,N}$, then

$$CW_{X1} = \sum_{i=1}^{N} W_{Xi} \tag{1}$$

But when the size of the tangle is very large, it becomes really difficult to recompute the weight of all the transactions in the past. Therefore to overcome this challenge, a new algorithm has been proposed to calculate the cumulative weight of the transactions using a fixed section of the DAG called subgraph [39].

C. Consensus Mechanism

Generating a level of trust among the nodes for the authenticity of the transactions is imperative for every distributed ledger technology. Since we want to trade energy, we will exchange currency in return. Also, to exchange highly sensitive data, we have to be sure that whether we want to depend on these trustless networks or not. In the traditional blockchain, the consensus is reached using a deterministic approach, i.e., the transaction will be valid in blockchain when a number of blocks are added in the chain. In IOTA, the consensus is reached i.e., tangle eventually is stochastic (or probabilistic). When almost all the participants in an IOTA network say that your transaction is more valid than this other transaction, then consensus will be achieved.

In the IOTA, the consensus is distributed in the tangle, and for placing one's own transaction in the network, the participant has to validate two past transactions, as discussed above. Apart from securing IOTA from the tip selection algorithm and cumulative weight-based consensus mechanism, a new security layer has been added to overcome the issue of conflicting tips. This security measure is called the shimmer, and it is a voting-based mechanism. Shimmer overcomes the drawbacks faced by traditional voting schemes. In this, the consensus for conflicting tip is achieved by proactive communication between the nodes.

IV. System Overview

Fig. 2 shows the detailed overview of the proposed V2G model. Initially, after the vehicles and grid join the network, they start with a message passing process. These messages are recorded on the IOTA tangle.

1) The first box shows the first step where the message passing takes place between the EVs and the grid users. The EVs can ask for energy from the grids or may offer for selling energy to the grids.
2) The second box shows the tangle creation to securely store the information that is being exchanged between the vehicles and the grid. The different transaction colors specify their cumulative weight. Once the transaction is verified by new transactions, the color becomes green. Initially, the color is kept as grey until the transaction is not verified.

3) The third box shows the process of Evolutionary Game Theory (EGT) being applied among the grids based on the energy price offered by the electric vehicles.
4) The fourth box shows the application of the Non-Cooperative Game Theory (NCGT) among the electric vehicles based on the selection probability given by grids.
5) Finally, a Stackelberg Game Theory (SGT) is applied to associate the best possible electric vehicle with the best possible grid, as shown in box 5 and 6.

A. Structure of V2G Network

In the proposed system model, a residential area, comprising of smart homes, EVs, smart supermarket, smart hospitals or any smart IoT device which can produce energy with the help of solar or wind panels, is considered. Every device, vehicle or grid, acts as a prosumer (both producer and consumer) in the model. The user acts as a buyer when he/she is in need of energy and is unable to meet the demand due to high consumption or unsteady generation. The seller, on the other hand, is one that has a surplus amount of energy. While generating and consuming electricity, expenses vary due to:

1) Climatic conditions: More electricity is consumed in the cold weather, and more of electricity is generated in the summer by PV panels.
2) Time of the day: Demand is increased in the morning when users are at home, and the output from PV panels is at its peak during midday.
3) Balanced electricity grid: To meet the high consumption requirements during peak-time, expenses should be higher than in off-peak time.

Every prosumer, either grid or vehicle, consists of a load and solar panel (SP). The SP of a prosumer is connected to the ac (Alternating Current) system and load through SP inverter (ac/dc converter). If a prosumer has both battery and SP installed, then can be connected via ac-coupled or dc-coupled topology. The battery is connected through the ac/dc converter to the ac side of the SP inverter in case of ac-coupled topology. In the dc-coupled topology, the battery is connected through the ac/dc converter at the dc side of the SP inverter.

All the vehicles and grid present in the residential area act as nodes of the IOTA network and can communicate with each other. A digital protocol known as the smart contract will be installed on the IOTA network, which will enforce the prosumer's energy management (PEM). Every time a user requests data or shares energy, the smart contract will run and facilitate the transaction. The data consisting of energy transactions, generation, and consumption of every prosumer, is stored at the IOTA network itself. The smart contract can be seen as an agent whose duty is to operate and store information regarding all the transactions that occurred during trading energy and the number of IOTA tokens sent during each transaction. We assume that the transmission cost and losses are very low or negligible since the amount of energy trading taking place in the V2G network is small. The main goal of this research is to develop an algorithm that assists in trading energy in the V2G network.

Let $\mathcal{A} = \{1, 2, 3, \ldots, i, \ldots, A\}$ be the set of $A \triangleq |\mathcal{A}|$ number of prosumers in a residential area with $i \in \mathcal{A}$. It is assumed that the total time of action is divided into equal intervals i.e., $\Delta t = 1$. Let $\mathcal{T} = \{1, 2, 3, \ldots, t, \ldots, T\}$ be the set of $T \triangleq |\mathcal{T}|$ number of time slots.

The solar power production profile of a prosumer i during a day can de defined as follows.

$$P_{\mathrm{sp},i} = \left\{P^1_{\mathrm{sp},i}, P^2_{\mathrm{sp},i}, P^3_{\mathrm{sp},i}, \ldots, P^T_{\mathrm{sp},i}\right\}, \quad i \in \mathcal{A} \tag{2}$$

where $P^1_{\mathrm{sp},i}$ refers to the solar power production by prosumer i in the first time slot. The consumption profile of prosumer i during that same time period is given as follows.

$$C_i = \left\{C^1_i, C^2_i, C^3_i, \ldots, C^T_i\right\}, \quad i \in \mathcal{A} \tag{3}$$

where C^1_i is the power consumption by prosumer i in the first time slot.

B. Electric Storage Units

Let $E^{t-\Delta t}_i$ and E^t_i be the energy level of the ESU of prosumer i at the beginning and end of the assumed time slot. Take $B^t_{\mathrm{cp},i}$ as the charging power of the ESU of prosumer i at time t and let $B^t_{\mathrm{dp},i}$ be the discharging power of the ESU of prosumer i at time t. It is assumed that the charging and discharging power of the ESU remain constant and the self-discharge of the ESU is neglected during time t. Let the Charging and discharging efficiency of the ESU for prosumer i be $\eta^t_{\mathrm{cp},i}$ and $\eta^t_{\mathrm{dp},i}$ respectively. Binary variables for prosumer i charging and discharging in time t are denoted by α^t_i and β^t_i, respectively. To avoid concurrent discharging and charging of the ESU, the sum of both the binary variables should be less than or equal to 1 i.e.,

$$\alpha^t_i + \beta^t_i \leq 1 \tag{4}$$

The energy stored during charging and discharging of the ESU is represented by ϕ^t_i and φ^t_i, respectively and is mathematically modeled as follows [30].

$$\phi^t_i = \alpha^t_i B^t_{\mathrm{cp},i} \eta^t_{\mathrm{cp},i} \Delta t \tag{5}$$

$$\varphi^t_i = \frac{\beta^t_i B^t_{\mathrm{dp},i} \Delta t}{\eta^t_{\mathrm{dp},i}} \tag{6}$$

where each time slot's length is denoted by Δt. Hence the total energy stored in the ESU can be modeled as:

$$E^t_i = E^{t-\Delta t}_i - \left(\varphi^t_i - \phi^t_i\right) \tag{7}$$

In practical scenarios, size of SP inverter decides the maximum and minimum limit of charging power and discharging power and the limits are given as follows:

$$0 \leqslant B^t_{cp,i} \leqslant B^{\max}_{cp,i}, 0 \leqslant B^t_{dp,i} \leqslant B^{\max}_{dp,i} \tag{8}$$

In the above equation, the maximum charging power is represented by $B^{\max}_{cp,i}$ and the maximum discharging power is represented by $B^{\max}_{dp,i}$. The cost of the ESU, the vehicle's wear and tear cost and the cost of purchased energy are the three primary factors in the computation of the cost of the V2G network. The use of ESUs will benefit V2G networks if and only if the ESU's cost per day i.e., CD is less than the corresponding cost saving.

TABLE II
LIST OF ACRONYMS

Notation	Meaning
CW	Cumulative Weight of the transaction
W_X	weight of transaction X
$\mathcal{A}$	Total number of prosumers in a residential area
$\mathcal{T}$	Total action time
P_{sp}	Production of prosumer
C	Consumption of prosumer
E_i^t	Energy level of ESU for prosumer i at time t
$B_{cp,i}^t$	Charging Power of ESU for prosumer i at time t
$B_{dp,i}^t$	Discharging Power of ESU for prosumer i at time t
$\eta_{cp,i}^t$	Charging Efficiency of ESU for prosumer i at time t
$\eta_{dp,i}^t$	Discharging Efficiency of ESU for prosumer i at time t
α_i^t	Binary variable related to charging of ESU
β_i^t	Binary variable related to discharging of ESU
ϕ_i^t	Energy stored during charging of ESU
φ_i^t	Energy stored during discharging of ESU
CD	Cost per Day of ESU
ω	Degradation cost of EV
$\mathcal{L}_\mathcal{T}$	ESU's lifetime throughput energy
$\mathcal{M}$	Prosumers who becomes sellers at time t
$\mathcal{N}$	Prosumers who becomes buyers at time t
ζ_i^t	Production-to-consumption ratio
$B_{s,m}^t$	Power that prosumer m sells at time t
$B_{b,n}^t$	Power that prosumer n buys at time t
$\mathcal{V}^t$	Amount of energy delivered to grid at time t
$\mathcal{G}^t$	Amount of energy required by grid at time t
p	Prosumer level of power consumption
ξ	Constant value depends upon prosumer
$\mathcal{U}(p,\xi)$	Utility function for prosumer
$\mathcal{W}(p,\xi)$	Welfare function for prosumer
$\mathcal{R}_m$	Supply to Demand ratio of prosumer
$\mathcal{D}_m$	Demanded energy from electric vehicle m
$\mathcal{Q}_m^t$	Probability of selecting electric vehicle m at time t
u_m^t	Net utility of electric vehicle m at time t
$\overline{u}^t$	Average Net utility of electric vehicles $\mathcal{M}$
ϖ_m^t	Price given by electric vehicle m at time t
x	Iteration number in EGT
y	Iteration number in NCGT

If the total saving done in a day is not more than the daily cost, use of ESU will not be justified. The CD is given as:

$$\text{CD} = \frac{1}{Y_d}\left[\mathcal{MC} + \frac{(1+r)^l r}{(1+r)^l - 1} \times \mathcal{CU}\right] \tag{9}$$

where Y_d represents tthe number of days in a year, $\mathcal{MC}$ represents the cost of maintaining the ESU annually, r is the interest rate for financing ESUs, l is the ESU's lifetime in years and $\mathcal{CU}$ is the combined cost of converter and ESU. The EV's wear and tear cost in V2G can be calculated as the degradation cost ω [40] due to extra running time:

$$\omega = \frac{\mathcal{CU}}{\mathcal{L}_\mathcal{T}} \tag{10}$$

where $\mathcal{L}_\mathcal{T}$ is the ESU's lifetime throughput energy and is given as:

$$\mathcal{L}_\mathcal{T} = D_D * E_i^t * l \tag{11}$$

Depth-of-discharge D_D is another factor that describes the depth of the ESU's discharge. D_D should remain above a certain level at all time to increase the overall ESU's lifetime.

C. Classifying Buyers and Sellers

Let $\mathcal{M}$ and $\mathcal{N}$ denote the seller and buyer at time t respectively where index $m \in \mathcal{M}$, $n \in \mathcal{N}$ and $i \in \mathcal{A}$. $M \triangleq |\mathcal{M}|$ and $N \triangleq |\mathcal{N}|$ gives total number of sellers and buyers respectively at given time t.

The production-to-consumption ratio ζ_i^t for prosumer $i \in \mathcal{A}$ at time or in the time interval $t \in \mathcal{T}$ is given as:

$$\zeta_i^t = \frac{P_{\text{sp},i}^t}{C_i^t} \tag{12}$$

where ζ_i^t is greater than 1 for sellers and lower than 1 for buyers. The amount of power that prosumer $m \in \mathcal{M}$ can sell and $n \in \mathcal{N}$ can buy at time t are respectively given as:

$$B_{\text{s},m}^t = C_m^t\left(\zeta_m^t - 1\right) \tag{13}$$

$$B_{\text{b},n}^t = C_n^t\left(1 - \zeta_n^t\right) \tag{14}$$

In the proposed system model, we are considering only vehicles as sellers and grids as buyers, i.e., only V2G exchange is considered. However, a similar model can be used to accommodate vehicle-to-vehicle (V2V), grid-to-vehicle (G2V), and grid-to-grid (G2G) communications and trading. At any time t when the grid wants to consume energy from the vehicle, various constraints are to be considered. The minimum amount of energy that an EV $m \in \mathcal{M}$ should always have is represented by ϑ_{min}^t. The amount of energy the EV $m \in \mathcal{M}$ is carrying at time t is denoted as ϑ_m^t. Hence, the amount of energy delivered to grid $\mathcal{V}^t$ is calculated as follows.

$$\mathcal{V}^t = D_D\left(\vartheta_m^t - \vartheta_{min}^t\right) \tag{15}$$

Also, the amount of energy required by the grid $\mathcal{G}^t$ at time t is obtained as:

$$\mathcal{G}^t = \varrho - \varrho_n^t \tag{16}$$

where the total capacity of the grid is ϱ and the storage level of the grid at the time of energy trade is denoted as ϱ_n^t.

D. Utility and Welfare Function for Prosumer

Behaviour of each entity could be independent based on time, price, etc., in V2G system. Different parameters such as electricity price, weather conditions, and time of the day determine the energy demand of each user. The energy demand also varies with the type of user i.e., industrial users and residential users can have different opinions on the same electricity price. The utility function can analytically model the response of users to different prices. Let $\mathcal{U}(p,\xi)$ be the utility function for V2G network where p represents the user's level of power consumption and ξ represents a parameter that varies according to prosumers. The level of happiness or satisfaction when a user consumes some power is represented by a utility function. Consumers are generally modeled using quadratic utility functions [41], [42] and logarithmic utility functions [43]–[46]. To calculate the satisfaction level of prosumer $i \in \mathcal{A}$ in time $t \in \mathcal{T}$, the quadratic utility function is given as:

$$\mathcal{U}\left(p_i^t, \xi_i^t\right) = \begin{cases} \dfrac{\xi^t}{\kappa_i} & \text{if } p_i^t \geqslant \dfrac{\xi_i^t}{\kappa_i} \\ p_i^t \xi_i^t - \left(p_i^t\right)^2 \dfrac{\kappa_i}{2} & \text{if } 0 \leqslant p_i^t \leqslant \dfrac{\xi_i^t}{\kappa_i} \end{cases} \tag{17}$$

where κ_i is a predefined constant. The welfare function $\mathcal{W}(p, \xi)$ for prosumer $i \in \mathcal{A}$ at time $t \in \mathcal{T}$ is given as follows.

$$\mathcal{W}\left(p_i^t, \xi_i^t\right) = \mathcal{U}\left(p_i^t, \xi_i^t\right) - p_i^t \varpi_i^t \tag{18}$$

where ϖ_i^t represents the price imposed by the seller.

V. Game Theory in V2G Network

In the proposed model, the smart grid acts as multiple buyers and EVs as multiple sellers. The Evolutionary Game Theory (EGT) model is used to select the best possible EV to buy energy from. EGT focuses more on the dynamics of change in the strategy. There is a competition among the grids, and to resolve the competition, EGT is used as the grids are constantly changing strategies to earn more profit. Another level of competition lies between the EVs. A Non-Cooperative Game Theory (NCGT) model is used to settle this competition. All the EVs are competing with each other to sell the energy to the grid at the best possible price. There is no cooperation among the EVs, and therefore NCGT is the best suitable model for this interaction. Further, a Stackelberg Game Theory (SGT) model is used for the interactions between the buyers and sellers. In the Stackelberg game model, the leader moves first and, based on the move of the leader, the follower decides its move. Therefore, to cater the interaction between EVs and the grid, a Stackelberg game is used.

A. Selection of Appropriate EV Using EGT

The population group $n \in \mathcal{N}$ in the proposed EGT model consists of all smart grids and they act as buyers. Once the EVs display their prices, each grid chooses an EV from which it will buy energy. The selection strategy of a grid is gradually adjusted and the EV is selected by the grid in an independent way during the process of selection. The probability that the EV $m \in \mathcal{M}$ is chosen by the grid $n \in \mathcal{N}$ in the t^{th} hour is given by $\mathcal{Q}_m^t$. The ratio of supply and demand for EV m at time t is given as follows.

$$\mathcal{R}_m = \frac{B_{\mathrm{s},m}^t}{D_m} \tag{19}$$

where D_m is the energy demand coming to EV m from the grid and $i \in \mathcal{A}$. The value of D_m used in the above equation is calculated as follows.

$$D_m = \mathcal{Q}_m^t \sum_{m=1}^{\mathcal{M}} p_i^{t*} \tag{20}$$

where

$$p_i^{t*} = \underset{p_i^t}{\arg\max} \mathcal{W}\left(p_i^t, \xi_i^t\right) \tag{21}$$

when the value of $\mathcal{R}_m$ is less than 1, then the true value of the power that the grid buys from the EV is

$$p_{i,true}^t = \mathcal{Q}_m^t \mathcal{R}_m p_i^{t*} \tag{22}$$

and when the value of $\mathcal{R}_m$ is greater than or equal to 1, then the true value of the power that the grid buys from the EV is:

$$p_{i,true}^t = \mathcal{Q}_m^t p_i^{t*} \tag{23}$$

The sum of the welfares of all grids obtained from EV m gives the net utility of grid n. When $B_{\mathrm{s},m}^t$ is greater than or equal to the demand D_m, the net utility is given as:

$$u_m^t = \frac{1}{2} \sum_{m=1}^{\mathcal{M}} \kappa_n \left(p_i^{t*}\right)^2 + Z \tag{24}$$

and when $B_{\mathrm{s},m}^t$ is less than the demand D_m, the net utility is given as:

$$u_m^t = \left[\mathcal{R}_m - \frac{\left(\mathcal{R}_m\right)^2}{2}\right] \sum_{m=1}^{\mathcal{M}} \kappa_n \left(p_i^{t*}\right)^2 + Z \tag{25}$$

where

$$Z = P_n^t \left(\xi_n^t - \frac{\kappa_n}{2} P_n^t\right) \tag{26}$$

We design replicator dynamics to depict the buyers' selection dynamics:

$$\frac{\partial \mathcal{Q}_m^t}{\partial t} = \mathcal{Q}_m^t \left(u_m^t - \overline{u}^t\right) \tag{27}$$

where $\overline{u}^t$ is defined as the average utility obtained as:

$$\overline{u}^t = \sum_{m=1}^{\mathcal{M}} u_m^t \mathcal{Q}_m^t \tag{28}$$

At stable conditions, the probability of selecting a seller will be fixed and the net utility of each EV will be equal to the average utility $\overline{u}^t$. Hence,

$$\frac{\partial \mathcal{Q}_m^t}{\partial t} = 0 \tag{29}$$

Using equation (26), (27) and (28), we get:

$$\frac{\partial \sum_{m=1}^{\mathcal{M}} \mathcal{Q}_m^t}{\partial t} = \overline{u}^t \left[1 - \sum_{m=1}^{\mathcal{M}} \mathcal{Q}_m^t\right] \tag{30}$$

Hence $\sum_{m=1}^{\mathcal{M}} \mathcal{Q}_m^t = 1$ and Lyapunov theory can prove the stable condition stated in equation (28) using the dynamics designed in equation (26). The equilibrium state in EGT is represented by:

$$\mathcal{Q}^{t*} = \left[\mathcal{Q}_1^{t*}, \mathcal{Q}_2^{t*}, \mathcal{Q}_3^{t*}, \ldots, \mathcal{Q}_{\mathcal{M}}^{t*}\right] \tag{31}$$

The approximation of replicator dynamics can be found in an iterative manner with the help of discrete the replicator as follows:

$$\mathcal{Q}_m^t(x+1) = \mathcal{Q}_m^t(x) + \sigma_1 \mathcal{Q}_m^t(x) \left(u_m^t(x) - \overline{u}^t(x)\right) \tag{32}$$

The criteria for its termination is given as:

$$\left|u_m^t(x) - \overline{u}^t(x)\right| < C \tag{33}$$

Algorithm 1: Algorithm for Selecting EV Using EGT.

Input: Price from EVs $\varpi_1^t, \varpi_2^t, \varpi_3^t, \ldots, \varpi_m^t$
Output: State of equilibrium $\mathcal{Q}^{t*} = [\mathcal{Q}_1^{t*}, \mathcal{Q}_2^{t*}, \mathcal{Q}_3^{t*}, \ldots, \mathcal{Q}_{\mathcal{M}}^{t*}]$
Initial probability assigned randomly by grid to EVs such that $\sum_{m=1}^{\mathcal{M}} \mathcal{Q}_m^t(1) = 1$;
$x = 0$;
repeat
  $x = x + 1$;
  for all $m \in \mathcal{M}$ **do**
    Calculate $\mathcal{R}_m(x)$ as per equation (19);
    Calculate p_i^{t*} as per equation (21);
    if $\mathcal{R}_m(x) \geqslant 1$ **then**
      Calculate u_m^t as per equation (24);
    else if $\mathcal{R}_m(x) < 1$ **then**
      Calculate u_m^t as per equation (25);
    end if
  end for
  Calculate $\overline{u}^t$ as per equation (28);
  As per equation (32) update discrete replicator;
until ($|u_m^t(x) - \overline{u}^t(x)| > C$);

where C is a small positive number, σ_1 is the adjustment parameter and x is the number representing iteration.

B. EVs Using NCGT for Maximizing Own Benefit

Since EVs run independently and do not form coalitions with other EVs, they use NCGT and behave reasonably. When $B_{\mathrm{s},m}^t$ is less than or equal to the demand D_m, then welfare function of EV is given as

$$\mathcal{W}\left(p_m^t, \xi_m^t\right) = \mathcal{U}\left(p_m^t, \xi_m^t\right) + \varpi_m^t B_{\mathrm{s},m}^t \tag{34}$$

and when $B_{\mathrm{s},m}^t$ is greater than the demand D_m, the welfare function of EV is given as

$$\mathcal{W}\left(p_m^t, \xi_m^t\right) = \mathcal{U}\left(p_m^t, \xi_m^t\right) + \varpi_m^t D_m \tag{35}$$

The total electricity sold and its price is included in the solution of the game and is also called as Nash equilibrium (NE). There are some set of conditions that need to be satisfied for the NE to exist in the NCGT. First, the set of players should be finite. Here we have $\mathcal{M}$ EVs, so this condition is always satisfied. For a fixed value of price i.e., ϖ_m^t, the welfare $\mathcal{W}(p_m^t, \xi_m^t)$ changes and buyers can purchase all the power available for export. If $B_{\mathrm{s},m}^t$ is greater than the demand D_m, then

$$\frac{\partial^2 \mathcal{W}(p_m^t, \xi_m^t)}{\partial\left(\varpi_m^t\right)^2} = -2\xi_m^t \sum_{n=1}^{\mathcal{N}} \frac{1}{\kappa_n} < 0 \tag{36}$$

When $B_{\mathrm{s},m}^t$ is less than or equal to the demand D_m, then

$$\frac{\partial^2 \mathcal{W}(p_m^t, \xi_m^t)}{\partial\left(\varpi_m^t\right)^2} = 0 \tag{37}$$

When all the demand of energy coming to EV D_m is completed or all the power $B_{\mathrm{s},m}^t$ is sold, the game is stopped. Using equations (35) and (36), we can say $\frac{\partial^2 \mathcal{W}(p_m^t, \xi_m^t)}{\partial(\varpi_m^t)^2} \leqslant 0$. Hence, the welfare functions are quasi-concave and continuous. Therefore, we come to the conclusion that the NE among EV exists in NCGT.

Algorithm 2: Algorithm for SE Between EV and Grid.

Input: EVs strategy at the initial stage
Output: State of stackelberg equilibrium
for all t in $\mathcal{T}$ **do**
  Initialize $\varpi^t(1), \varpi_1^t(1), \varpi_2^t(1), \varpi_3^t(1), \ldots, \varpi_m^t(1)$;
  $y = 0$;
  repeat
    $y = y + 1$;
    Run Algorithm 1
    Calculate demand $D_m(y)$ as per equation (20);
    Send $D_m(y)$ to every EV m
    As per equation (38) and (40) update price of energy;
  until ($|D_m(y) - B_{\mathrm{s},m}^t| > C$);
end for

C. SGT Between EV and Grid

SGT can be used between the EVs as multiple leaders and the grids as multiple followers. The output of the EGT i.e., the probability of selecting a seller and the output of the NCGT i.e., the price for energy are the inputs to the NCGT and EGT, respectively. This relationship between EGT and NCGT is established using SGT. An EV announces the price which is received by all the grids and they participate in EGT. The output of the EGT gives the probability of selecting a seller which is used by EVs to acquire a NE and update their prices. The NE can't be obtained analytically since EVs are using NCGT and all the EVs are unknown to each other. Therefore Stackelberg equilibrium (SE) in SGT and NE among EVs is reached with the help of an iterative algorithm. The strategy followed by EV m to update its price is given as:

$$\varpi_m^t(y+1) = \varpi_m^t(y) + \sigma_2\left(D_m(y) - B_{\mathrm{s},m}^t\right) \tag{38}$$

The criteria for its termination is given as:

$$\left|\varpi_m^t(y+1) - \varpi_m^t(y)\right| < C \tag{39}$$

Equation (39) can also be written as:

$$\left|D_m(y) - B_{\mathrm{s},m}^t\right| < C \tag{40}$$

where C is a small positive number, σ_2 is an adjustment parameter, and y is the number of iterations. The first step in energy trading is EVs announcing the price of energy, which is then received by the grid, and then they play the EGT. Grids reach equilibrium for the price announced by EVs using EGT, and they send this information back to EVs. When EVs receive this strategy from grids, they engage in a NCGT to update their prices, and this is repeated until equilibrium is obtained. This is how V2G energy trading takes place using game theory in an effective manner.

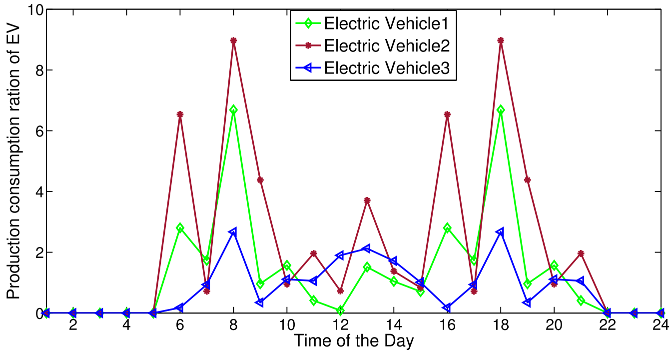


Fig. 3. PCR of all EVs.

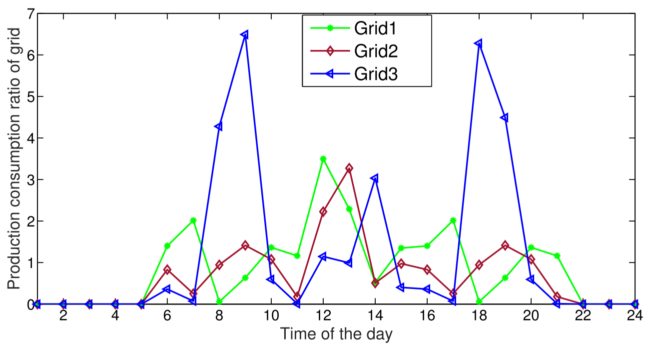


Fig. 4. PCR of all grids.

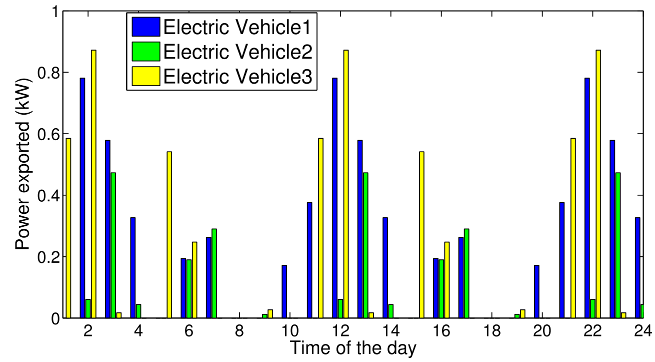


Fig. 5. Total power that Electric Vehicle can export.

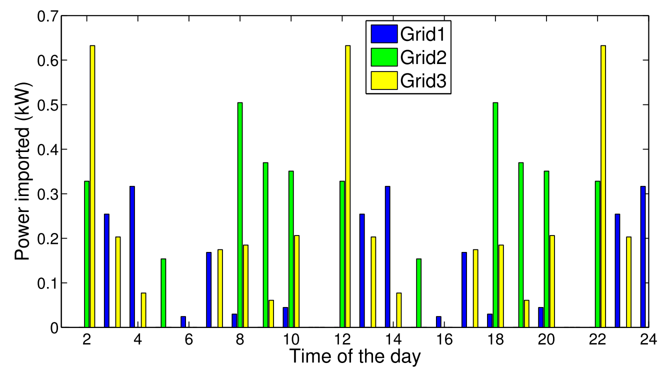


Fig. 6. Total power imported by grids.

VI. Numerical Analysis

A. Simulation Settings

For assessing the performance of energy trading in the V2G community, the simulation results are presented in this section. In our model, we have considered a community of 3 grids and 10 EVs. Each EV is equipped with a PV solar system and can trade energy with grids in exchange for iota tokens. For one day $\mathcal{T} = \{1, 2, \ldots, 24\}$ is time under consideration. The production profiles and load of EVs and grids are taken from [47]. The buying and selling prices of electricity are detremined based on the actual prices of electricity in the USA. Charging and discharging power limits of the ESUs are set to 3 kW. The charging and discharging efficiency of the ESUs are set to 0.6 and 0.4, respectively.

B. Performance Evaluation

Results generated by the methods used in the paper are compared and evaluated in this section. Fig. 3 shows the Power Consumption Ratio (PCR) of all Electric Vehicles at each hour of the day. Meanwhile, Fig. 4 shows the PCR of all grids at each hour of the day. It is important to study the PCR values in order to understand the actual time when the model will be highly in use. The demand and supply of energy and the rate at which the energy has to be sold or bought is also dependent on the production and consumption of energy. Electric Vehicles can sell the excess energy when the value of $PCR > 1$ at any time slot $t \in \mathcal{T}$ for $i \in \mathcal{A}$. Grids can buy energy from EVs when the value of $PCR \leqslant 1$ at any time slot $t \in \mathcal{T}$ for $i \in \mathcal{A}$.

Fig. 5 shows the total amount of power (in kW) that Electric Vehicles can export at any time t of the day. The amount of energy over time that Electric Vehicles can sell to grids depends on the amount of energy present with Electric Vehicles after they meet their own requirements. It can be observed from the graph that different electric vehicles have a different amount of energy that they can sell at different times of the day. It depends on the energy generated by the EV and its requirements. Taxi vehicles might have less energy to sell compared to personal vehicles that are used less often. Fig. 6 shows the amount of power (in kW) that grids imported from Electric Vehicles. The amount of energy over time that the grid buys from Electric Vehicles depends on the requirement of the grid. Also, the grid can meet certain requirements by itself as it also has its own generation from the PV panels installed on buildings, roofs.

Fig. 7 shows the convergence characteristics of EGT versus the number of iterations. It can be observed from the graph that the Electric Vehicles initially change their energy price over a few iterations and then stop changing the prices. The change in price becomes stable once the EVs reach maximum possible utility. The change in price by Electric Vehicles is due to a change of their selection probability by the grid. Once the price provided by the EVs becomes stable, the grid submits the selection probability to the EVs, and the non-cooperative game starts between the EVs to trade energy with the grid. Fig. 8 shows the variations in the selection probability of a grid for energy trade versus the number of iterations. It can be

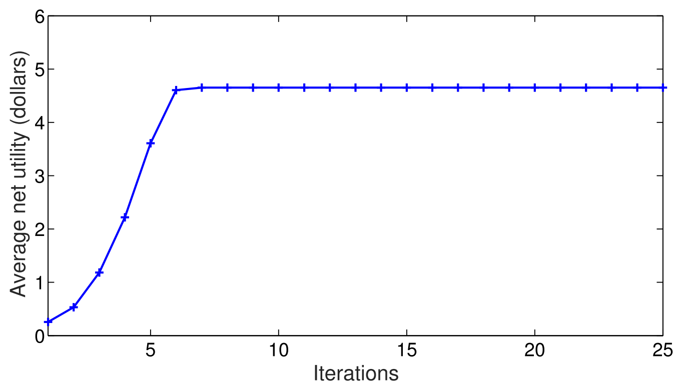


Fig. 7. Average net utility of all EVs.

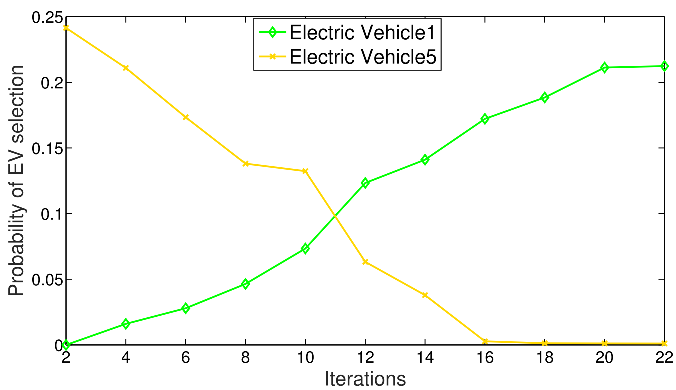


Fig. 8. Probability of selecting Electric Vehicles versus number of Iterations.

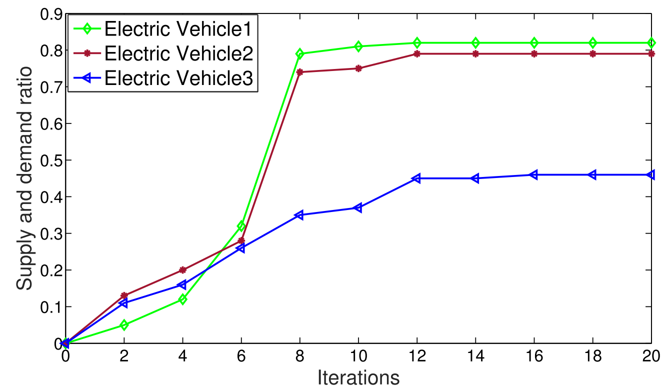


Fig. 9. Ratio of supply and demand of Electric Vehicles.

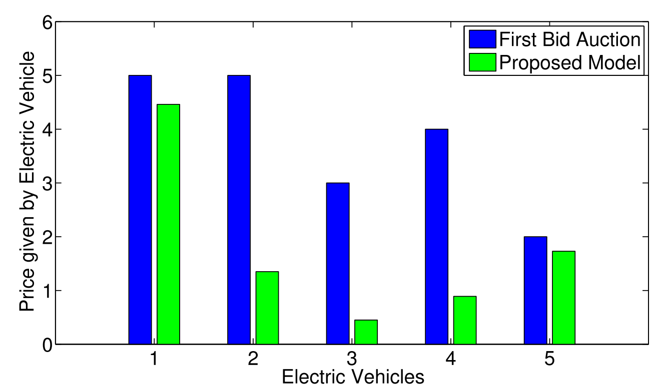


Fig. 10. Comparison of price between first Bid auction and proposed model.

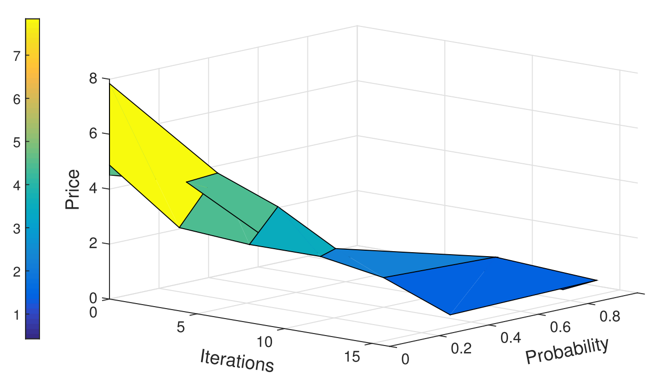


Fig. 11. Variation of probability and price over iterations.

observed from the graph that, in contrast to Electric Vehicle, the probability that the grid selects Electric Vehicle 1 is increasing as the iterations increases. This is so because the change in price by Electric Vehicle 1 is more convenient to the grid compared to the change in price by Electric Vehicle 5. This makes the grid increase the probability of selecting Electric Vehicle 1, and decrease the probability of selecting Electric Vehicle 5. The traditional schemes do not have the option of changing the prices as per demand and supply, and therefore the overall revenue of both parties is low compared to the proposed scheme, where both parties are allowed to choose the best possible option.

Fig. 9 shows the change in supply to demand ratio of three different Electric Vehicles versus the number of iterations. The supply of energy is adjusted by the electric vehicles in such a way that the supply to demand ratio $\mathcal{R}_m$ increases with the iterations. The increase in the supply to demand ratio increases the selection probability of the EVs and also increases the overall revenue of the EVs.

Fig. 10 shows a comparison of the price given by five Electric Vehicles in the first bid auction and proposed model. It can be observed that the price given by electric vehicles is reduced in the proposed model, which results in the welfare of the grid. Since the genuine price is being offered by the EVs, the selection probability by the grid increases. Therefore, the overall welfare and revenue of the EVs are also enhanced.

Fig. 11 shows a change in price given by Electric Vehicles versus the probability of Electric Vehicle selection versus the number of iterations. It can be observed from the graph that as the price given by Electric Vehicles decreases, the probability of getting selected by the grid increases and vice-versa. The values on the color map show the change in color on the graph with the change in the value of price by EVs.The yellow color shows the maximum price and minimum selection probability, and the dark blue color shows the minimum price and maximum selection probability.

VII. Conclusion

In this paper, we have proposed a scheme for trading energy in V2G networks using iota as the distributed ledger. Three game-theoretic models were applied for price competition among EVs and negotiation of selection between grids and EVs. A tangle data structure is used for the purpose of recording all the transactions in a secure manner. Moreover, evolutionary game theory is proposed, which uses an iterative algorithm that helps grids choose a suitable EV for energy trading. Meanwhile, a non-cooperative game is used to allow the EVs to compete with each other. Finally, Stackelberg game is used to allow negotiation between the grid and EVs. In this context, a Nash Equilibrium is acquired using these game-theoretic models. Simulation results presented prove that the proposed algorithm helps EVs and grids achieve a stable state, where the revenue of both parties is enhanced. The work can be further extended to G2V, G2G, and V2V networks.

Acknowledgment

The authors gratefully acknowledge the support of NVIDIA Corporation with the donation of the Titan Xp GPU used for this research. The authors are also thankful to Pranav Goyal for his support in the completion of the project as an intern at BITS, Pilani.

References

[1] H. Farhangi, "The path of the smart grid," *IEEE Power Energy Mag.*, vol. 8, no. 1, pp. 18–28, Jan. 2010.

[2] W. Kempton and S. E. Letendre, "Electric vehicles as a new power source for electric utilities," *Transp. Res. D: Transport Environ.*, vol. 2, no. 3, pp. 157–175, 1997.

[3] L. Gan, U. Topcu, and S. H. Low, "Optimal decentralized protocol for electric vehicle charging," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 940–951, May 2013.

[4] S. Garg, K. Kaur, S. H. Ahmed, A. Bradai, G. Kaddoum, and M. Atiquzzaman, "MobQoS: Mobility-aware and QoS-driven SDN framework for autonomous vehicles," *IEEE Wireless Commun.*, vol. 26, no. 4, pp. 12–20, August 2019.

[5] S. Garg, K. Kaur, G. Kaddoum, S. H. Ahmed, and D. N. K. Jayakody, "SDN-based secure and privacy-preserving scheme for vehicular networks: A 5G perspective," *IEEE Trans. Veh. Technol.*, vol. 68, no. 9, pp. 8421–8434, Sep. 2019.

[6] M. Kiaee, A. Cruden, and S. Sharkh, "Estimation of cost savings from participation of electric vehicles in vehicle to grid (V2G) schemes," *J. Modern Power Syst. Clean Energy*, vol. 3, no. 2, pp. 249–258, 2015.

[7] W. Tushar, W. Saad, H. V. Poor, and D. B. Smith, "Economics of electric vehicle charging: A game theoretic approach," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 1767–1778, Dec. 2012.

[8] W. Tushar, C. Yuen, H. Mohsenian-Rad, T. Saha, H. V. Poor, and K. L. Wood, "Transforming energy networks via peer to peer energy trading: Potential of game theoretic approaches," *IEEE Sig. Process. Mag.*, vol. 35, no. 4, pp. 90–111, 2018.

[9] W. Tushar, B. Chai, C. Yuen, D. B. Smith, K. L. Wood, Z. Yang, and H. V. Poor, "Three-party energy management with distributed energy resources in smart grid," *IEEE Trans. Ind. Electron.*, vol. 62, no. 4, pp. 2487–2498, Mar. 2015.

[10] R. Mohsenian, H. Amir, V. W. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 320–331, Dec. 2010.

[11] S. Nakamoto, "Bitcoin: A peer-to-peer electronic cash system," 2008. [Online]. Available: http://bitcoin.org/bitcoin.pdf

[12] S. Garg *et al.*, "Edge computing-based security framework for big data analytics in VANETs," *IEEE Netw.*, vol. 33, no. 2, pp. 72–81, Mar. 2019.

[13] Y. Zhang, C. Xu, N. Cheng, H. Li, H. Yang, and X. S. Shen, "Chronos+: An accurate blockchain-based time-stamping scheme for cloud storage," *IEEE Trans. Services Comput.*, vol. 13, no. 2, pp. 216–229, Mar.–Apr. 2020.

[14] Y. Zhang, C. Xu, J. Ni, H. Li, and X. S. Shen, "Blockchain-assisted public-key encryption with keyword search against keyword guessing attacks for cloud storage," *IEEE Trans. Cloud Comput.*, to be published, doi: 10.1109/TCC.2019.2923222.

[15] V. Hassija, V. Chamola, V. Saxena, D. Jain, P. Goyal, and B. Sikdar, "A survey on IoT security: Application areas, security threats, and solution architectures," *IEEE Access*, vol. 7, pp. 82 721–82 743, Jul. 2019.

[16] M. Walport *et al.*, "Distributed ledger technology: Beyond blockchain," *UK Government Office for Science*, vol. 1, 2016.

[17] W. Jiang, H. Li, G. Xu, M. Wen, G. Dong, and X. Lin, "PTAS: Privacy-preserving thin-client authentication scheme in blockchain-based PKI," *Future Gener. Comput. Syst.*, vol. 96, pp. 185–195, 2019.

[18] T. Alladi, V. Chamola, J. J. Rodrigues, and S. A. Kozlov, "Blockchain in smart grids: A review on different use cases," *Sensors*, vol. 19, no. 22, 2019, Art. no. 4862.

[19] T. Alladi, V. Chamola, B. Sikdar, and K.-K. R. Choo, "Consumer IoT: Security vulnerability case studies and solutions," *IEEE Consum. Electron.*, vol. 9, pp. 6–14, 2019.

[20] S. Popov, "The tangle," Jun. 17, 2019. [Online]. Available: https://assets.ctfassets.net/r1dr6vzfxhev/2t4uxvsIqk0EUau6g2sw0g/45eae33637ca92f85dd9f4a3a218e1ec/iota1_4_3.pdf

[21] V. Hassija, V. Saxena, and V. Chamola, "Scheduling drone charging for multi-drone network based on consensus time-stamp and game theory," *Comput. Commun.*, vol. 149, pp. 51–61, 2020.

[22] G. Bansal, V. Hassija, V. Chamola, N. Kumar, and M. Guizani, "Smart stock exchange market: A secure predictive decentralised model," in *Proc. IEEE Globecom*, Waikoloa, USA, Dec. 2019, pp. 1–6.

[23] R. Zhang, X. Cheng, and L. Yang, "Energy management framework for electric vehicles in the smart grid: A three-party game," *IEEE Commun. Mag.*, vol. 54, no. 12, pp. 93–101, Dec. 2016.

[24] S. Zou, Z. Ma, X. Liu, and I. Hiskens, "An efficient game for coordinating electric vehicle charging," *IEEE Trans. Autom. Control*, vol. 62, no. 5, pp. 2374–2389, May 2017.

[25] Z. Liu, Q. Wu, S. Huang, L. Wang, M. Shahidehpour, and Y. Xue, "Optimal day-ahead charging scheduling of electric vehicles through an aggregative game model," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 5173–5184, Sep. 2018.

[26] 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. Inform.*, vol. 13, no. 6, pp. 3154–3164, Dec. 2017.

[27] S.-C. Oh, M.-S. Kim, Y. Park, G.-T. Roh, and C.-W. Lee, "Implementation of blockchain-based energy trading system," *Asia Pacific J. Innov. Entrepreneurship*, vol. 11, no. 3, pp. 322–334, 2017.

[28] E. Mengelkamp, B. Notheisen, C. Beer, D. Dauer, and C. Weinhardt, "A blockchain-based smart grid: Towards sustainable local energy markets," *Comput. Sci.-Res. Develop.*, vol. 33, no. 1–2, pp. 207–214, 2018.

[29] M. Andoni *et al.*, "Blockchain technology in the energy sector: A systematic review of challenges and opportunities," *Renewable Sustain. Energy Rev.*, vol. 100, pp. 143–174, 2019.

[30] S. Garg, K. Kaur, G. Kaddoum, F. Gagnon, and J. J. P. C. Rodrigues, "An efficient blockchain-based hierarchical authentication mechanism for energy trading in V2G environment," in *Proc. IEEE Int. Conf. Commun. Workshops*, May 2019, pp. 1–6.

[31] E. Sortomme and K. W. Cheung, "Intelligent dispatch of electric vehicles performing vehicle-to-grid regulation," in *Proc. IEEE Int. Electric Vehicle Conf.*, Mar. 2012, pp. 1–6.

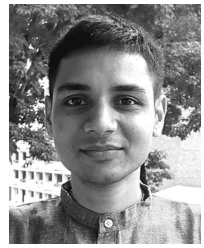
[32] W. Lee, L. Xiang, R. Schober, and V. W. Wong, "Electric vehicle charging stations with renewable power generators: A game theoretical analysis," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 608–617, Mar. 2015.

[33] Y. Wang, W. Saad, Z. Han, H. V. Poor, and T. Başar, "A game-theoretic approach to energy trading in the smart grid," *IEEE Trans. Smart Grid*, vol. 5, no. 3, pp. 1439–1450, May 2014.

[34] N. Kumar, S. Misra, N. Chilamkurti, J.-H. Lee, and J. J. Rodrigues, "Bayesian coalition negotiation game as a utility for secure energy management in a vehicles-to-grid environment," *IEEE Trans. Dependable Secure Comput.*, vol. 13, no. 1, pp. 133–145, Jan./Feb. 2016.

[35] R. Yu, J. Ding, W. Zhong, Y. Liu, and S. Xie, "PHEV charging and discharging cooperation in V2G networks: A coalition game approach," *IEEE Internet Things J.*, vol. 1, no. 6, pp. 578–589, Dec. 2014.
[36] S. Garg, K. Kaur, G. Kaddoum, and K.-K. R. Choo, "Towards secure and provable authentication for Internet of Things: Realizing industry 4.0," *IEEE Internet Things J.*, vol. 7, no. 5, pp. 4598–4606, May 2020.
[37] C. Harbor, "IOTAs tangle powers IAMPASS biometric palm vein authentication for digital identity," Jun. 2019. [Online]. Available: https://blog.iota.org/iotas-tangle-powers-iampass-biometric-palm-vein-authentication-for-digital-identity-3cd0acef8bd9
[38] E. Hop, "How iota addresses are generated from seeds," Jun. 2019. [Online]. Available: https://medium.com/iota-demystified/how-iota-addresses-are-generated-from-seeds-40f554e38818
[39] J. Cech, "IRI 1.5.0ŁŁNew tip selection algorithm and other improvements," Jun. 2019. [Online]. Available: https://blog.iota.org/new-tip-selection-algorithm-in-iri-1-5-0-61294c1df6f1
[40] W. Kempton and J. Tomić, "Vehicle-to-grid power fundamentals: Calculating capacity and net revenue," *J. Power Sources*, vol. 144, no. 1, pp. 268–279, 2005.
[41] S. Maharjan, Q. Zhu, Y. Zhang, S. Gjessing, and T. Başar, "Demand response management in the smart grid in a large population regime," *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 189–199, Jan. 2016.
[42] B. Chai, J. Chen, Z. Yang, and Y. Zhang, "Demand response management with multiple utility companies: A two-level game approach," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 722–731, Mar. 2014.
[43] N. Liu, M. Cheng, X. Yu, J. Zhong, and J. Lei, "Energy-sharing provider for pv prosumer clusters: A hybrid approach using stochastic programming and Stackelberg game," *IEEE Trans. Ind. Electron.*, vol. 65, no. 8, pp. 6740–6750, Aug. 2018.
[44] J. Lee, J. Guo, J. K. Choi, and M. Zukerman, "Distributed energy trading in microgrids: A game-theoretic model and its equilibrium analysis," *IEEE Trans. Ind. Electron.*, vol. 62, no. 6, pp. 3524–3533, Jun. 2015.
[45] H. Wang, T. Huang, X. Liao, H. Abu-Rub, and G. Chen, "Reinforcement learning in energy trading game among smart microgrids," *IEEE Trans. Ind. Electron.*, vol. 63, no. 8, pp. 5109–5119, Aug. 2016.
[46] S. Maharjan, Q. Zhu, Y. Zhang, S. Gjessing, and T. Basar, "Dependable demand response management in the smart grid: A Stackelberg game approach," *IEEE Trans. Smart Grid*, vol. 4, no. 1, pp. 120–132, Mar. 2013.
[47] N. Liu, X. Yu, C. Wang, C. Li, L. Ma, and J. Lei, "Energy-sharing model with price-based demand response for microgrids of peer-to-peer prosumers," *IEEE Trans. Power Syst.*, vol. 32, no. 5, pp. 3569–3583, Sep. 2017.

Vikas Hassija received the B.Tech. degree from Maharshi Dayanand University, Rohtak, India, in 2010, and the M.S. degree in telecommunications and software engineering from the Birla Institute of Technology and Science, Pilani, India, in 2014. He is currently working toward the Ph.D. degree in IoT security and blockchain with the Jaypee Institute of Information and Technology, Noida, India, where he is currently an Assistant Professor. He has eight years of industrial experience and has worked with various telecommunication companies, such as Tech Mahindra and Accenture. His research interests include the IoT security, network security, blockchain, and distributed computing.



Vinay Chamola received the B.E. degree in electrical and electronics engineering and the master's degree in communication engineering from the Birla Institute of Technology and Science, Pilani, India, in 2010 and 2013, respectively, and the Ph.D. degree in electrical and computer engineering from the National University of Singapore, Singapore, in 2016. In 2015, he was a Visiting Researcher with the Autonomous Networks Research Group, University of Southern California, Los Angeles, CA, USA. He is currently an Assistant Professor with the Department of Electrical and Electronics Engineering, BITS-Pilani, Pilani, India. His research interests include green communications and networking, 5G network management, Internet of Things, and Blockchain.

Sahil Garg received the Ph.D. degree from the Thapar Institute of Engineering and Technology, Patiala, India, in 2018. He is currently a Postdoctoral Research Fellow with École de technologie supérieure, Université du Québec, Montréal, QC, Canada. He has many research contributions in the area of machine learning, big data analytics, security and privacy, Internet of Things, and cloud computing. He has authored or coauthored more than 50 publications in high ranked journals and conferences, including more than 20 IEEE Trans./Journal papers. Some of his research findings are published in top-cited journals such as IEEE TII, IEEE TCC, IEEE TMM, IEEE TVT, IEEE TNSM, IEEE TSUSC, IEEE IoT Journal, IEEE Systems Journal, *IEEE Communications Magazine*, *IEEE Network Magazine*, IEEE Wireless Communications, *IEEE Consumer Electronics Magazine*, FGCS, JPDC, *Applied Soft Computing*, and *Information Sciences*, including various international conferences of repute such as-IEEE Globecom, IEEE ICC, IEEE WCNC, IEEE CCNC, IEEE VTC, IEEE Infocom Workshops, ACM MobiCom Workshops, ACM MobiHoc Workshops, etc. He was the recipient of prestigious Visvesvaraya Ph.D. fellowship from the Ministry of Electronics & Information Technology under Government of India (2016–2018). For his research, he has also been awarded the IEEE ICC Best Paper Award in 2018 at Kansas City, USA. He serves as a Managing Editor for Springer's *Human-centric Computing and Information Sciences* (HCIS) and an Associate Editor for Wiley's *International Journal of Communication Systems* (IJCS). He has been a Lead Guest Editor for a number of special issues in prestigious journals and magazines, such as IEEE TII, IEEE T-ITS, IEEE IoT Journal, IEEE Network, and Elsevier's FGCS. He also serves as a General and Publicity Chair for workshops, including IEEE Infocom, IEEE Globecom, and IEEE ICC. He is a member of IEEE Communications Society, IEEE Computer Society, IEEE Industrial Electronics Society, IEEE Software Defined Networks Community, IEEE Smart Grid Community, ACM, and IAENG.

Dara Nanda Gopala Krishna is currently working toward the B.Tech. degree with the Jaypee Institute of Information and Technology, Noida, India. He is currently a Summer Intern with Birla Institute of Technology and Science, Pilani, India. He has completed few projects on blockchain applications and machine leaning. His research interests include distributed computing, the IoT, and data analytics.

Georges Kaddoum received the bachelor's degree in electrical engineering from the École Nationale Suprieure de Techniques Avancées (ENSTA Bretagne), Brest, France, the M.S. degree in telecommunications and signal processing (circuits, systems, and signal processing) from the Université de Bretagne Occidentale and Telecom Bretagne (ENSTB), Brest, France, in 2005, and the Ph.D. degree (with Hons.) in signal processing and telecommunications from the National Institute of Applied Sciences (INSA), University of Toulouse, Toulouse, France, in 2009. He is currently an Associate Professor and Tier 2 Canada Research Chair with the École de Technologie Supérieure (ÉTS), Université du Québec, Montréal, QC, Canada. In 2014, he was awarded the ÉTS Research Chair in physical-layer security for wireless networks. Since 2010, he has been a Scientific Consultant in the field of space and wireless telecommunications for several US and Canadian companies. He has authored or coauthored more than 170 journal and conference papers and has two pending patents. His recent research activities cover mobile communication systems, modulations, security, and space communications and navigation. He received the best papers awards at the 2014 IEEE International Conference on Wireless and Mobile Computing, Networking, Communications (WIMOB), with three coauthors, and at the 2017 IEEE International Symposium on Personal Indoor and Mobile Radio Communications (PIMRC), with four coauthors. Moreover, he received IEEE TRANSACTIONS ON COMMUNICATIONS Exemplary Reviewer Award for the year 2015 and 2017. In addition, he received the Research Excellence Award of the Université du Québec in the year 2018. In the year 2019, he received the Research Excellence Award from the ÉTS in recognition of his outstanding research outcomes. He is currently serving as an Associate Editor for the IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY, and IEEE COMMUNICATIONS LETTERS.

Dushantha Nalin K. Jayakody (Senior Member, IEEE) received the Ph.D. degree in electronics, electrical, and communications engineering from the University College Dublin, Dublin, Ireland, in 2014, and the M.Sc. degree in electronics communications engineering from the Department of Electrical and Electronics Engineering, Eastern Mediterranean University, Famagusta, Turkey, in 2010 (under the University full graduate scholarship). From 2014 to 2016, he was a Postdoc Research Fellow with the Institute of Computer science, University of Tartu, Estonia, and the Department of Informatics, University of Bergen, Norway. Since 2016, he has been a Professor with the School of Computer Science & Robotics, National Research Tomsk Polytechnic University (TPU), Russia. He is currently the Head of Research and Educational center on Automation and Information Technologies and is a Founder of Tomsk Infocom Lab, TPU, Tomsk, Russia. In addition, since 2019, he has been the Head of the School of Postgraduate & Research, Sri Lanka Technological Campus (SLTC), Padukka, Sri Lanka, and the Founding Director of the Centre of Telecommunication Research, SLTC. He is currently supervising eight Ph.D. students and many master's and undergraduate students. He spent a short research stays with the Centre for Telecommunications Research, University of Sydney, Australia, in 2015, and Texas A&M University in 2018. He has authored/coauthtored more than 120 international peer-reviewed journal and conference papers and books. His research interests include PHY and NET layer prospective of 5G communications technologies, such as NOMA for 5G, etc., cooperative wireless communications, device-to-device communications, LDPC codes, unmanned aerial vehicle, etc. Prof. Jayakody is a recipient of the Best Paper Award from the IEEE International Conference on Communication, Management and Information Technology (ICCMIT) in 2017 and the International Conference on Emerging Technologies of Information and Communications, Bhutan, in March 2019. In July 2019, he was also the recipient of the Education Leadership Award from the World Academic Congress in 2019. In 2017 and 2018, he received the outstanding faculty award by National Research Tomsk Polytechnic University, Russia. He also received the Distinguished Researcher award in *Wireless Communications* from International Journal for Research Under Literal Access, India, in 2019. He has organized or co-organized more than 20 workshops and special sessions of various IEEE conferences. He also served as Chair, Session Chair, or Technical Program Committee Member for various international conferences, such as IEEE PIMRC from 2013 to 2019, IEEE WCNC from 2014 to 2018, IEEE VTC from 2015 to 2018, etc. He is currently an Area Editor for the Elsevier *Physical Communications* Journal, MDPI *Information* journal, and Wiley *Internet of Technology Letters*. In his career, so far, he has attracted nearly $6M research funding. Also, he is a Reviewer for various IEEE Transactions and other journals.