AN EFFICIENT DECENTRALIZED SECURE ENERGY MANAGEMENT FRAMEWORK FOR SMART GRID SYSTEM

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CERTIFICATE

I, Shubhani Aggarwal, Regn. No. 901703015, hereby declare that the thesis entitled **“An Efficient Decentralized Secure Energy Management Framework for Smart Grid System"** submitted to the Computer Science and Engineering Department at Thapar Institute of Engineering & Technology, Patiala, Punjab, India is an authenticated record of my own work for the award of the degree of "Doctor of Philosophy" under the supervision of Prof. (Dr.) Neeraj Kumar. This report has not been submitted to any other institution for award of any other degree.

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ABSTRACT

Over the last few decades, emerging technologies (such as Big Data Analytics, Cloud Computing, Software Defined Networks, *etc.*) necessitated a paradigm shift from a traditional centralized communication infrastructure to decentralized one. In such a setup, billions of Internet-enabled devices are interconnected in an environment popularly known as *Internet-of-Things (IoT).* the number of such interconnections reduces the computational overhead and complexity by distributing the workload among geo-located nodes. However, it may generate various types of security threats and challenges due to the usage of an open channel *i.e.,* the Internet. The security threats such as denial-of-service, eavesdropping, man-in-the-middle, *etc.* are dependent on authorization, authentication, and accountability (AAA) methods used in the IoT environment. Extensible authentication protocol (EAP) is one of the popular authentication protocols used to mitigate these attacks in an IoT environment. Also, the transport layer security (TLS) and secure socket layer (SSL) are necessary protocols used along EAP for establishing a secure communication channel between various smart devices in this environment. However, the aforementioned schemes are built using a centralized architecture or heavily rely on central decision-making authority, raising issues of a single point of failure and long delay.

From the above discussion, it is clear that security and privacy are the major concerns for the successful implementation of any solution in such an environment. Moreover, the evolution of technologies as mentioned above make it difficult to capitalize the existing centralized security mechanism to handle the diverse requirements of geo-dispersed ecosystems (edge computing, smart grid, intelligent transportation systems, *etc.*) To overcome these issues, blockchain technology is being used that provides identity privacy and transaction security using a decentralized and dependable architecture. It is a peer-to-peer (P2P) technology to provide security and privacy to the users by using various types of consensus mechanisms between different geo-located nodes present on the network. It is a trusted network in which all the nodes are anonymous to each other such that each node has its own ledger to store the history of the transactions.

Blockchain is an emerging technology that consists of a chain of digital signatures in a cryptographic system. A distributed ledger technology (DLT) provides security, integrity, confidentiality, and non-repudiation for real-time applications that a centralized system may not provides. Therefore, it is one of the most powerful technologies to provide secure and dependable energy services to different distributed smart communities like vehicle-to-grid (V2G). V2G technology plays an important role in balancing the energy demand and supply between electric vehicles (EVs) and the service providers (SPs) for demand response management in smartgrid systems. But, there are challenges of security and privacy preservation, data manipulation, transparency, in V2G environments due to conventional centralized mechanisms. Hence, it may increase the energy gap between demand and supply. Hence, there is a requirement for a distributed mechanism to stabilize the energy demand and supply between consumers and prosumers in smart grid systems. In the aforementioned challenges, the research work focused on two problems existing in smart grid systems: (i) an efficient incentive-based energy trading scheme between EVs and SPs, (ii) a secure and decentralized demand response management scheme in smart grid systems. This task has been accomplished in the research work with two different theories such as game theory and auction theory.

By gaining knowledge from the study, we designed a P2P energy trading model using blockchain technology. This model represents the energy coins transferred from an energy buyer's wallet address to the energy seller's wallet address after the energy exchanges between them. The memory pool of energy aggregators (EAG) has the latest energy blockchain data for verifying the payment transaction. The new transaction records generated by the energy buyers are uploaded to EAGs for auditing, which is further verified and digitally identified by the energy sellers. Therefore to obtain the proper balance between demand and supply on blockchain energy, we implement incentives that reassure energy nodes to fulfil the energy demands out of self-interest. As per the duration of an energy trading, the energy seller is rewarded with energy coins with the contribution of energy exchanges between them. The Proof-of-Authority (PoA) consensus mechanism is used on a blockchain to verify and validate the energy transactions between the energy sellers and buyers.

The first approach presents a P2P energy trading scheduling (PETS) scheme. Using this scheme, an energy trading problem is formulated using the PETS scheme between EVs and the SPs in smart grid systems. The PETS scheme is modelled as incentive-based so that more EVs and SPs can participate in energy trading. It provides a high level of security to the users' private information. Then, the Stackelberg game theory as 1-leader multi-followers is proposed to model the interactions between EVs and the SPs. Moreover, as per the announced price by the leader SP, EVs schedule the battery and manage the energy consumption by minimizing their energy bills. We use a genetic algorithm in smart grid systems to optimize energy bills and maximize SP's profit.

The second approach presents the demand response management scheme between EVs and the SPs in smart grid systems. To stabilize the smart grid and manage and control EVs' ever-growing energy demands, we are formulating an energy trading problem as non-linear, which maximizes the social welfare between the EVs and the SPs. Then, to solve the problem of demand response between them, a double auction algorithm is designed in a V2G environment to manage the EVs' private information by rational and weak balanced budget (WBB) properties. A consortium blockchain-based framework is designed to ensure secure energy transactions between them without a trusted third-party authenticator. Moreover, the energy pricing and the amount of traded energy problems for demand response are solved by auction mechanisms that maximize social welfare among the nodes.

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List of Abbreviations

Abbreviations	**Definitions**
AMI	Advanced metering infrastructure
BFT	Byzantine fault tolerance
CIM	Common information model
DDOS	Distributed denial-of-service
DDPG	Deep deterministic policy gradients
DNO	Distributed network operator
DOS	Denial-of-service
DDoS	Delegated Proof-of-stake
DR	Demand response
DSO	Distributed system operator
DSIC	Dominant-strategy-incentive-compatibility
DLT	Distributed Ledger Technology
EAG	Energy aggregators
EAP	Extensible authentication protocol
EBP	Energy buyer problem
EE	Energy efficiency
ESP	Energy seller problem
EVs	Electric vehicles
IBR	Inclining block rate
ID	Identity
ICT	Information and communication technology
IoT	Internet-of-Things
IoE	Internet-of-Energy
IR	Individual rationality
IT	Information technology
KWh	Kilowatt hour
LCoE	Levelized costs of electricity
MDP	Markov decision process
MILP	Mixed integer linear programming
MINLP	Mixed integer non-linear programming
MITM	Man-in-the-middle

NPV	Net present value
NP	Non-polynomial
ns	Nanoseconds
OAP	Optimal allocation problem
PAR	Peak-to-average ratio
PBFT	Practical byzantine fault tolerance
PET	Power and electronics technology
PHEVs	Plug-in hybrid electric vehicles
PK	Private key
PKI	public key infrastructure
PoA	Proof-of-Authority
PoW	Peer-of-work
PoS	Peer-of-stake
P2P	Peer-to-Peer
PPO	Proximal policies optimal
PSO	Particle swarm optimization
PU	Public key
PV	Photovoltaic
QoS	Quality-of-service
RERs	Renewable energy resources
RCB	Rate of convergence of buyer
RCS	Rate of convergence of seller
RTP	Real-time pricing
SAO	Service oriented architecture
SDN	Software-defined networking
SQL	Structured query language
SPs	Service Providers
SWM	Social welfare maximization
TF	Truthfullness
ToU	Time of use
V2G	Vehicle-to-Grid
WBB	Weak balanced budget

Chapter 1

Introduction

Over the last few decades, the rapid advancements in information and communication technology (ICT) have given an exponential increase in smart device usage, resulting in the demand for one of the most popular technologies called the Internet of things (IoT). It refers to the ever-growing network of connected physical objects using the Internet. It consists of billions of connected objects to provide many services like e-healthcare, smart transportation, smart grid systems, and smart sensing, to name a few, to the end-users. In such an environment, the bulk amount of data is generated from these heterogeneous and graphically distributed devices. Michael Kanellos and Vernon Turner described the statistics in their report [1] that approximately 80 billion devices will be connected to the Internet by 2025. They also described that the total amount of digital data generated worldwide would be 4.4 Zettabytes in 2013 to 180 Zettabytes by 2025, as shown in Fig. 1.1. They also proved that currently connected devices per person are greater than the world population and are increasing exponentially as shown in Fig. 1.2. From the above-mentioned facts, we found that the transmission of the massive amount of data and information to the core platform requires security and privacy. This information is shared using an open channel, *i.e.*, the Internet. In addition, it is also efficient for processing and storing data in the cloud repository. However, the cloud systems are not found to be trustworthy as the global ecosystem has witnessed an exponential in the number of attacks such as replay attacks, distributed denial-of-service (DDoS), data modification, and eavesdropping. The dependability of cyber security mechanisms has increased manifold to handle this situation. There are many solutions to manage different cyber-attacks on several applications such as smart grids, healthcare, voting system, *etc*. However, the need for ubiquitous services in various applications on the move creates hurdles in front of the existing security solutions for many attacks. Fig. 1.3 shows the growth trend of some of the recent attacks in various domains.

However, communication over an open channel means security and privacy are two key concerns we need to address [2]. Many security solutions have been designed by the researchers, which are generally based on a centralized architecture. Such architectures rely on a trusted third-party authenticator to provide security and privacy in the smart communities such

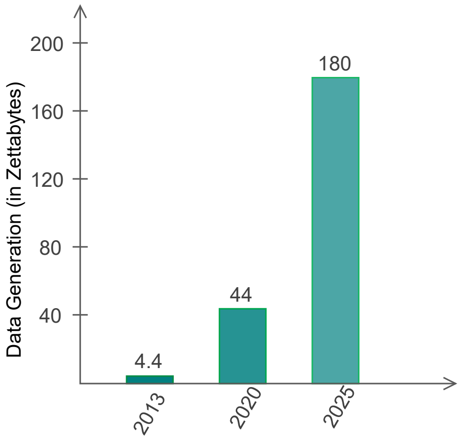


Figure 1.1: Digital data generation from the smart devices

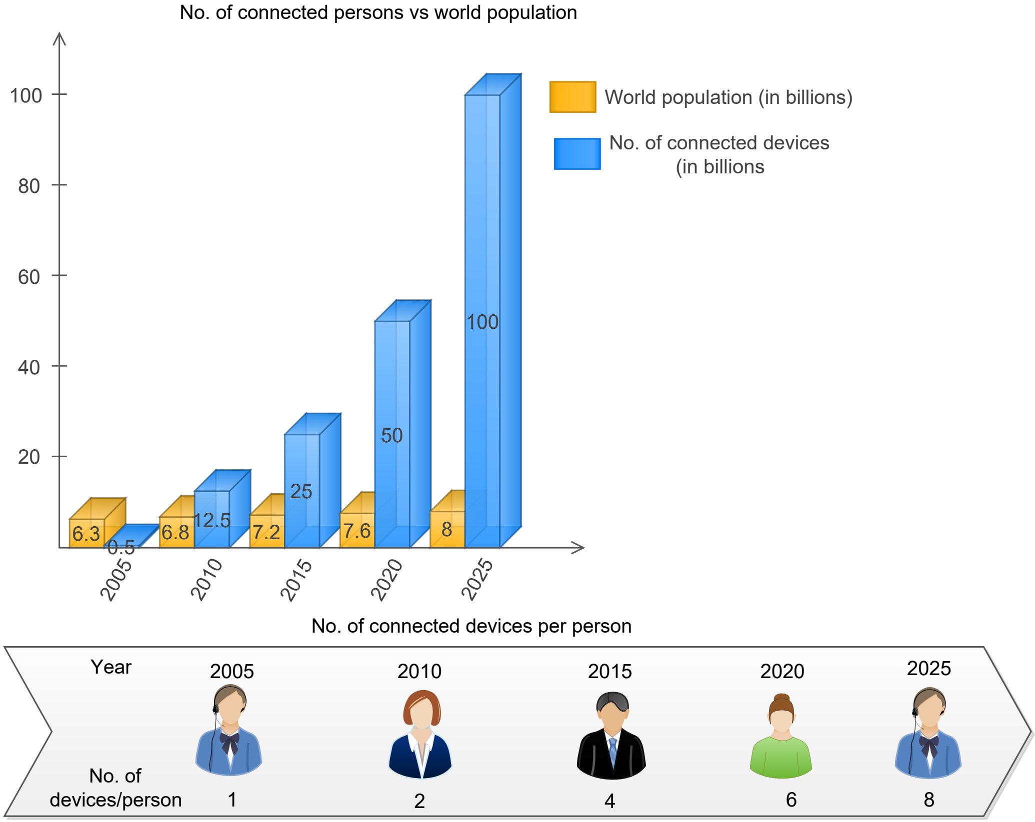


Figure 1.2: No. of connected devices per person vs world population

as healthcare system, smart grid system, transportation system, which may leads to a single point of failure and have other known limitations. Also, in a centralized system, every node is connected with a central authority that authenticates and authorizes the transmission data. Hence, anonymity and privacy leakage are two ongoing challenges in such systems. For example, in an industrial sector, an adversary can gain control and forecasts fabricated generation

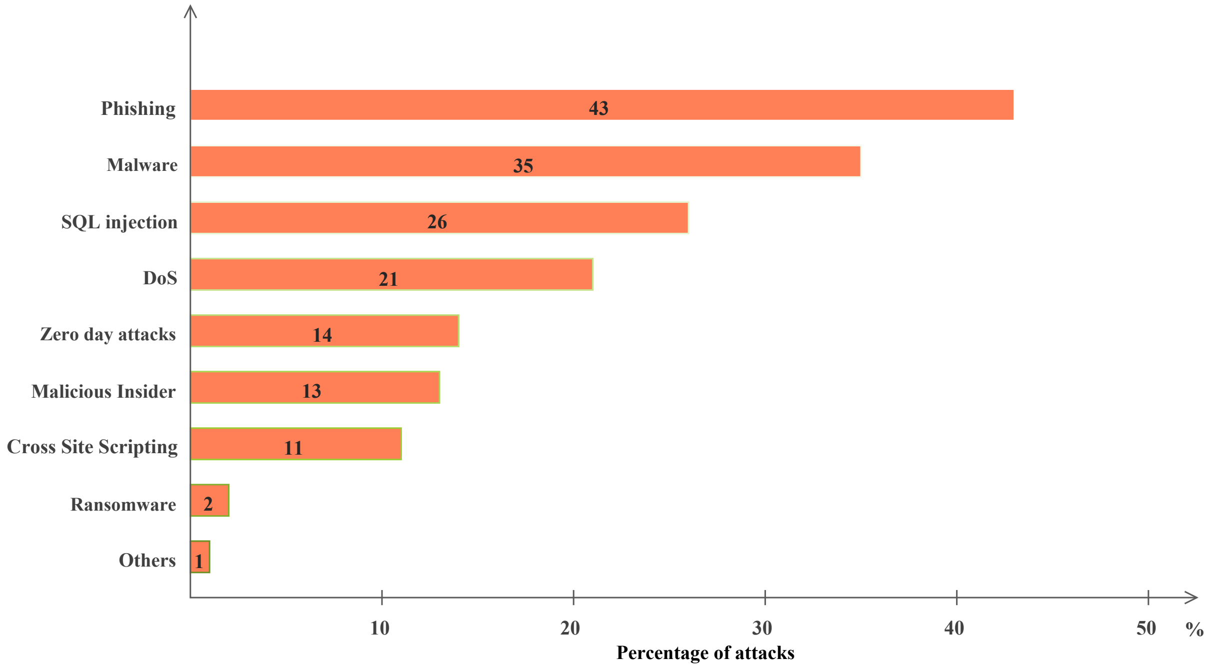


Figure 1.3: Cyber-attacks

data, which in turn leads to misleading price fluctuations. Also, in the smart energy ecosystem, a malicious entity can tamper the load profiles of consumers and can lead to frivolous energy bills. Moreover, an adversary can gain access to confidential consumer data, which can lead to serious consequences and penalties.

From the above-discussion, it is clear that security and privacy are the major concerns for the successful implementation of any solution in smart communities [3]. Further, the evolution of technologies make it difficult to capitalize the existing centralized security mechanisms to handle the diverse requirements of geo-dispersed ecosystems (edge computing, smart grid, intelligent transportation systems, *etc.*). Hence, there has been a shift towards designing decentralized systems to avoid the limitations inherent of a centralized architecture, where each node is connected with other nodes without involving a centralized authority.

1.1 Introduction to Smart Grid Systems

From the past few years, the power industry has gone through rapid changes, which lead to various revolutions in smart grid, micro-grid, and Vehicle-to-Grid (V2G) technology. These technologies have provided an extraordinary transformation from the traditional power grids to the smart grid with the integration of Internet and ICT. Also, digital technology allows bi-directional communication between the customers and service providers (SPs) along with sensing in transmission lines, which makes the power grid smart and is known as the "Smart Grid" [4, 5]. It consists of smart homes, SPs, electric vehicles (EVs), smart appliances, smart meters, renewable energy, consumer engagement, distribution intelligence, operation centres, and plug-in hybrid electric vehicles (PHEVs) to control and manage the smart grid data. It is also defined as a network of transmission lines, substations, transformers, and electricity distribution from one grid centre to the smart homes, buildings, and industries. It also provides an efficient way to transmit electricity to customers that reduces the peak demand of end-users, increases the integration of renewable energy resources, reduces operational and maintenance costs, and quick restoration after energy disturbances. Thus, it can be viewed as “basic building blocks” to support the energy requirements of both industrial and residential users.

V2G is an emerging technology in the smart grid that supports energy exchange between EVs and SPs. The power fluctuations by the diffusion of renewable energy resources in V2G are solved by EVs, which are being used in energy trading for demand response management [6,7]. A large number of EVs absorb an excessive amount of energy during off-peak time and get back the same energy to the grid during peak time. They provide an efficient and effective solution to smooth the peak load and balance the demand-supply mismatch in V2G energy trading scenarios [8]. On the other hand, the widespread popularity of EVs among consumers may impose a severe burden on V2G energy trading for demand response management. It is expected that by 2025, there will be around 8.4 million EVs on the road globally [9]. Thus, there is a need for a reliable solution to furnish future energy requirements of industrial and residential users while supporting EVs’ charging and discharging needs. Despite the above-mentioned advantages, the wide-area deployment of V2G still confronts several challenges as follows. Firstly, there is lacking a distributed security mechanism for V2G energy trading because traditional centralized mechanisms rely on a trusted third-party authenticator to manage and audit the energy transactions, which leads to a series of security threats such as denial of service attacks, data manipulation, and replay attacks. Secondly, there lacks an efficient V2G energy trading mechanism for demand response management. For example, authors in [10–13] proposed EVs charging and discharging scheme without considering security and privacy issues in V2G energy trading. They have announced the EV’s private information to all the participants and have assumed that this information is known to everyone in energy trading for demand response management. With this, EV’s long charging time and the limited navigating range make the V2G energy trading process more complicated. Without security and privacy concerns in V2G environments, connected entities (EVs and the SPs) can be hacked, and once hackers can gain control, they can tamper with the functionality of these entities by stealing the energy data. This can affect the overall functionality of various appliances used in this environment. The data, energy, and information shared by EVs and other V2G entities, such as the local aggregator, communication and authentication servers, billing centre, and control centre, must be secured [14,15]. So, there is a strong need to design a distributed security mechanism in V2G energy trading for demand response management, which can effectively maximize the economic benefits of EVs and SPs.

By gaining knowledge from the study, we designed a P2P energy trading model using blockchain technology. This model represents the energy coins transferred from an energy buyer's wallet address to the energy seller's wallet address after the energy exchanges between them. Therefore to obtain the proper balance between demand and supply on blockchain energy, we implement incentives that reassure energy nodes to fulfil the energy demands out of self-interest. As per the duration of an energy trading, the energy seller is rewarded with energy coins with the contribution of energy exchanges between them. The Proof-of-authority (PoA) consensus mechanism is used on a blockchain to verify and validate the energy transactions between the energy sellers and buyers.

1.2 Architecture of Energy Trading in Smart Grid Systems

A smart grid is considered a typical cyber-physical system. All the operations and mechanisms are controlled and managed by computer-based algorithms. For optimizing energy trading in the smart grid, there is a need for a secure data exchange among EVs and charging stations, distribution power systems, and reliable communication [16]. Based on the architecture of smart grid systems [17], and the framework for cyber-physical system [18], we present a four-layered architecture for energy trading mechanism in the smart grid, which is shown in Figure 1.4. The energy trading architecture includes energy trading layer, a data acquisition layer, a communication network layer, and a market layer described as follows.

1.2.1 Energy Trading Layer

The energy trading layer includes energy aggregators (advanced metering infrastructure (AMI), local aggregators), energy nodes (smart buildings, EVs, and charging stations), and smart meters. The energy aggregators work as energy brokers to manage an exchange of energy and provide communication services to the network. The energy nodes are machines in which energy can be stored or generated. Then, this energy is transported via transmission lines, substations, and transformers to the end-users. As per the architecture, energy nodes play different roles such as- energy buyers and sellers in smart grid systems' energy trading. Every node on this layer selects its role as per the current state of energy and future work plans. The consumed or used energy can be controlled and maintained by the smart meter used in the smart grid. The smart meter is an electronic device used to collect and calculate consuming and distributed energy records in real-time. Then, the consumers pay energy coins or money to the prosumers as per the energy records recorded on the smart meter. This layer is comprised of IoT devices used in smart grid functions, such as power generation, transmission, distribution and utilization.

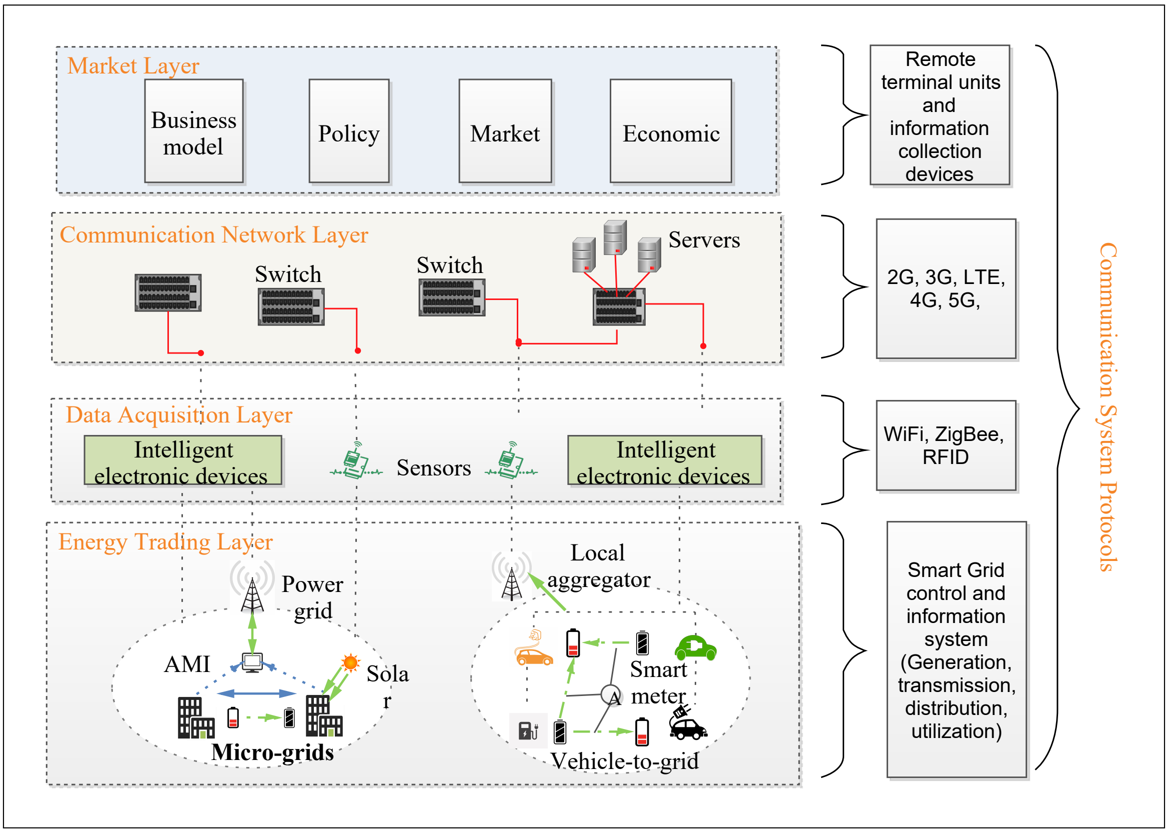


Figure 1.4: Architecture of smart grid systems

1.2.2 Data Acquisition Layer

This layer collects information on energy consumption and distribution from different energy nodes through sensors, intelligent electronic devices, and monitoring devices. As per the requirements of an application, we can use the data acquisition modules to work on this layer in smart grid systems. For example, sensors and electronic devices collect data such as-power density and equipment power on energy consumption in micro-grid environments. But in the case of V2G environments, sensors are used to monitor the battery status of EVs, such as- load, charging/ discharging status, temperature, current, *etc*. The communication protocols used in this layer are ZigBee, WiFi, which are used to transmit the collected data to a remote communication network layer.

1.2.3 Communication Network Layer

Information and communication technology (ICT) aims to support, control, coordinate, and manage an exchange of energy among EVs, charging stations, and the power grid. This layer facilitates the real-time exchange of energy between different energy nodes in the smart grid [19]. The communication infrastructure mainly includes connected devices, wired/wireless connections used for communicating information, servers, routers, circuits, switches, *etc*. It reduces the distance and makes the flow of information faster. It also saves time, budget, information, ideas, and opinions, which can be shared among different energy nodes at any given time. At this layer, the communication system protocols are 2G, 3G, 4G, LTE, 5G, 6G which are used to provide connectivity to the Internet [20].

1.2.4 Market Layer

This layer presents the business view of energy trading in the smart grid. It includes two parts, *i.e.*, (i) the wholesale market and (ii) the retail market. The primary role in the market domain are energy sellers, energy buyers, and the distribution system operator (DSO) worked as participants. The essential processes of this layer include bidding, decision-making, exchange of energy, and energy settlement. It also comprises all the financial and business-related aspects of energy trading. Energy market structures, the micro-economics of energy technologies, and energy billing belong to this layer. It also considered the various factors, such as- investments, net present value (NPV), Levelized costs of electricity (LCoE), electricity tariffs, and pricing mechanisms of energy trading in smart grid systems. It control and manages all the smart grid functions.

1.2.5 Interaction Among all Layers

This section defines the interaction among all the four layers used for energy in smart grid systems. From the users' layer, *i.e.,* the energy trading layer to the market layer, there is a need for the virtual energy market and physical energy network to enable energy trading in the smart grid. The physical energy network is used to exchange energy among various entities such as EVs, smart homes, charging stations, *etc.*, while the virtual energy market platform is required for selling and buying the energy in a local energy market. The interaction among four layers shows the number of research activities in the different disciplines. It attempts to define smart grids' critical elements for sustainable energy and flexibility. The architecture has been used for providing a market platform to consumers and prosumers with reliable and scalable energy trading. Their main advantages are enhancing system efficiency, reducing energy costs, and deferral of systems upgrades. The data acquisition layer uses sensors and electronic devices to efficiently and securely track energy information. Thus, passing this information to the market layer through switches and routers for the use of consumers. In this way, the communication and interaction among these layers will support the real-time energy exchange among various entities in the smart grid.

1.3 Cyber Security Challenges and Solutions in Smart Grid Systems

With ICT rising, which is the backbone of development, organizations and industries, observe the growing cyber security threats in the smart grid [21]. The primary cyber security challenges in the smart grid are as follows.

- Hacking: One of the most common cyber security threats is hacking. It is exploiting a private network or digital system to gain unauthorized information. The severity of its impact on the smart grid increases as hacking exposes sensitive data, leakage of private information of end-users, and causes major legal trouble.
- Phishing: This cyber security threat is sending out malicious files and deceitful communication that seems to be from an authentic source, but in reality, is meant to enter the system and harm the smart grid data.
- Man-in-the-Middle attack: This cyber security attack mostly happens when an attacker includes themselves in a two-party transaction as an authenticator. When the attacker successfully enters the traffic, he can interrupt communication channels and steal the smart grid's information.
- Structured Query Language (SQL) Injection: A SQL Injection is a cyber security threat that occurs when the attacker injects harmful code into the system, causing it to divulge information, which under normal circumstances it is not authorized to do.

The key to effectively tackling cyber security challenges are described as follows.

- Raise Awareness: Cyber security challenges are not stagnant. Every day, there is a new threat, and everyone must be sensitized to the issues. The end-users must follow safety protocols while dealing with the digital data in the smart grid.
- Prevent Database Exposure: Some standard methods to prevent smart meter database exposure are keeping physical hardware safe, having a web application firewall, encrypting server data, taking regular backups, and limited access to servers.
- Implement Strong Authentication: Not having enough authentication processes is a common source of cyber security threats. At least a 2-step verification process must be implemented to protect all devices from cyber security threats in smart grid systems.

Recently, blockchain technology with decentralization, privacy, security, and trust management has been introduced in V2G energy trading for demand response management. It enables energy trading to be executed in decentralized, transparent, private, and secure V2G market environments [22]. It is a chain of cryptographic blocks combined to form a Peer-to-Peer (P2P) network having the potential for creating and using the smart contract in a smart grid to ensure security and privacy to the energy transactions done between consumers and prosumers. It provides scalability, flexibility, reliability, authorization, identity management, data integrity, confidentiality, non-repudiation, authentication and accountability to the network [23]. Here, each node has its ledger for storing the history of the transactions. It provides immutability, auditability, cryptographic security, distributed ledgers, and transparency over the centralized system. The characteristics of blockchain technology are shown in Fig. 1.5.

The blockchain-based distributed network has two types: (i) a Permissioned network and (ii) a Permissionless network. In the former, the network owner decides the node that is assigned the rights to access, send, receive, join, and verify the block to create an agreement between the nodes. However, in the latter, everyone has the right to join, access, send, verify and receive the transactions of the blocks in the blockchain to create a consensus. The comparison between centralized and distributed ledger systems is as shown in Fig. 1.6.

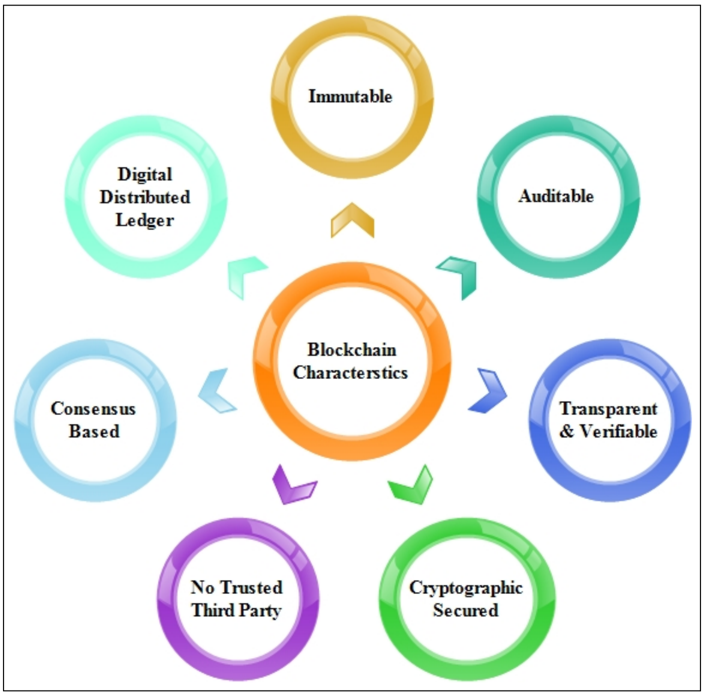


Figure 1.5: Characteristics of Blockchain

1.4 Blockchain Technology: Background, Architecture and Key Components

Blockchain technology is a trusted network in which all the nodes are anonymous to each other such that each node has its ledger used to store the history of transactions. Before moving on to how a blockchain is used in the smart community, it is important to discuss the background of bitcoin cryptocurrency and the key components of blockchain technology.

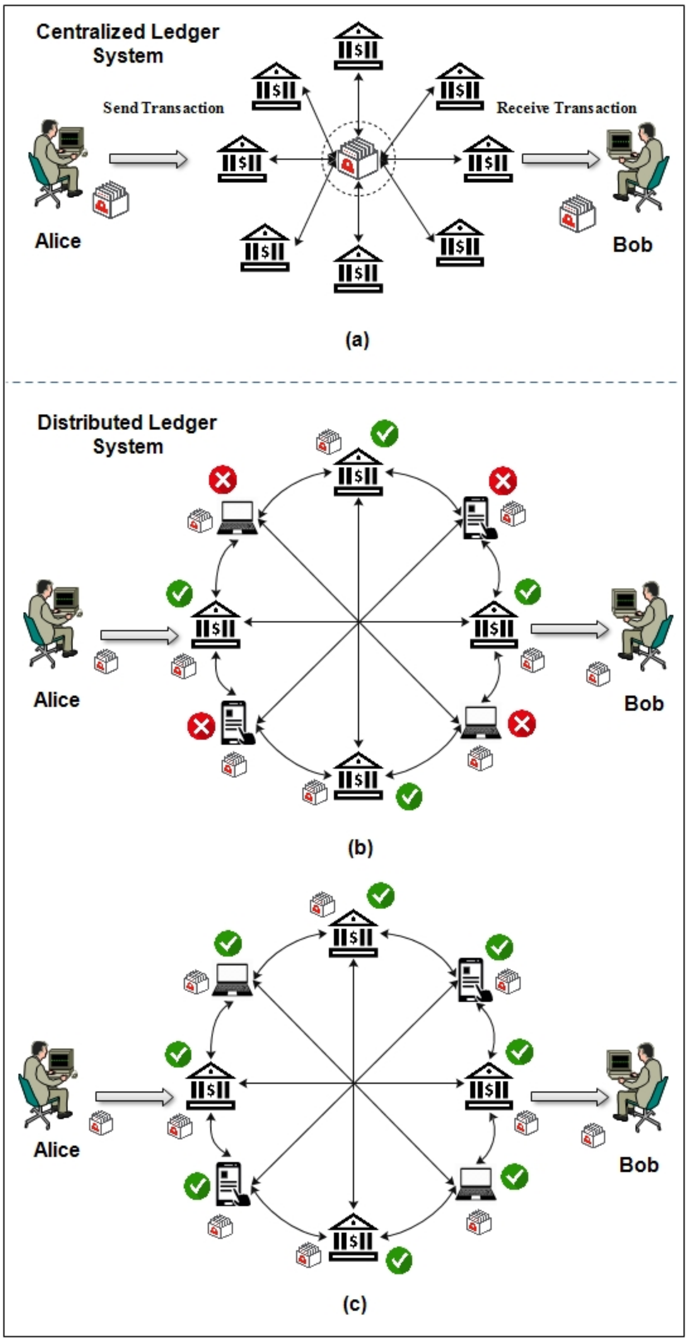


Figure 1.6: Comparison of centralized and distributed ledger systems (a) Centralized System (b) Permissioned (c) Permissionless

1.4.1 Types of Nodes in a Blockchain Network

The distributed nature of blockchain consists of two types of nodes that communicate with each other in a P2P manner in order to handle the transactions. The two types of nodes, Miner Node and Normal Node, are discussed below.

- **Miner nodes** are special nodes which are selected on the basis of some specific terms and policies. These are used to authenticate, verify, authorize and validate the blocks containing transactions in the network. They are rewarded in the form of bitcoins (or some cryptocurrency/‘gas’) for performing these operations.

- **Normal nodes** are ordinary nodes which have the full information of the blockchain in their ledger. They perform coordination and cooperation of the transactions which are authenticated by miner nodes in the network.

1.4.2 Network Model

The blockchain-based network model for the smart environment consists of several components which are described below.

- **Devices** consist of nodes, sensors, machines and servers in the blockchain network. These devices communicate, sense, and process the data using a gateway and routers.
- **Gateways** are used in the network for connecting ‘n’ devices. It provides connectivity to the network devices and facilitates additional functionality such as security, data collection, and data management.
- **Miner** nodes are used to authenticate and validate the transactions and data exchange using different consensus mechanism or protocols.
- **Smart Contract** is a protocol used to authorize the devices and to check that these devices do not operate beyond their limits. It provides a secure communication platform between various smart devices and the distributed network.
- **Consensus** is an agreement which is signed between the different nodes of the network. There are various type of consensus protocols used for agreement between the nodes, and popular ones used for consensus include Proof-of-Work (PoW), Proof-of-Stake (PoS), and Delegated Proof-of-Stake (DPoS).

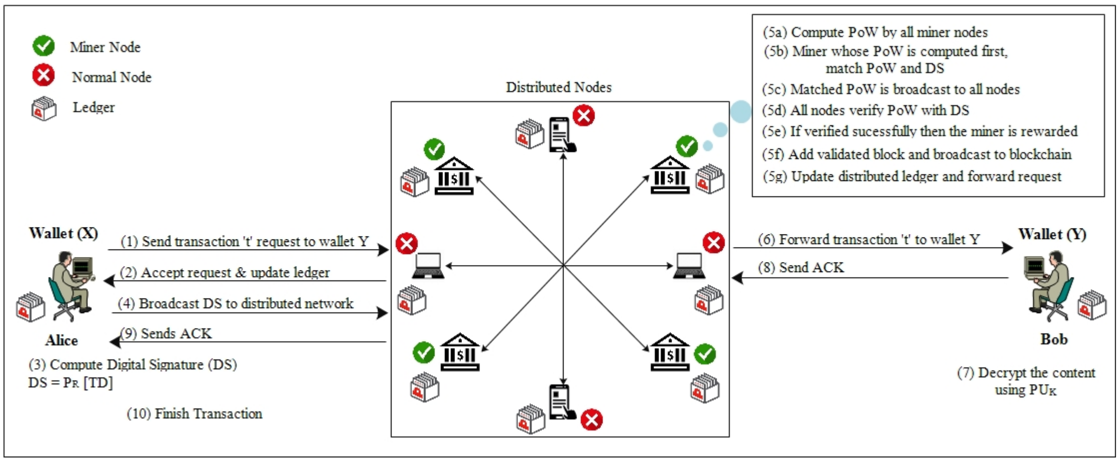


Figure 1.7: Bitcoin Transaction System

1.4.3 Bitcoin Transaction System

The flow of transactions in bitcoin is shown in Fig. 1.7, and discussed below.

- If Alice wants to send some coins from her wallet X to Bob's wallet Y, then a request of transactional data 't' is sent to Bob. This request is broadcasted in the entire network.
- The distributed nodes accept the request and update their ledgers with the transactional information of Alice-Bob.
- After updating ledgers, Alice computes digital signature (DS) and broadcasts it in the network. item A miner node is selected to verify and validate the transaction. It computes PoW to match the DS received. If PoW is successfully matched with DS, then the result is broadcast to all the nodes for verification and validation.
- The other miner nodes also verify the PoW with DS. If the verification is successful, then the miner node is (financially) rewarded for computing the PoW.
- The validated block is added in the validated chain and the transaction is broadcasted to the entire blockchain.
- Using the validated transaction 't', the bitcoins are added to wallet Y of Bob.
- Bob decrypts the content using the paired public key (PUK) of Alice and sends the acknowledgment (ACK) to Alice.
- The transaction is finished once Alice receives the transaction acknowledgment.

1.4.4 Blocks in a Blockchain

A block consists of a block header, policy header and content. A Blocker header contains the previous hash value generated by the PoW mechanism. The Policy header contains the information about the requestee (i.e. unique identity, source IP, destination IP, and the actions performed). Content consists of the transactions used for communication. The pictorial representation of blocks in a blockchain is shown in Fig. 1.8.

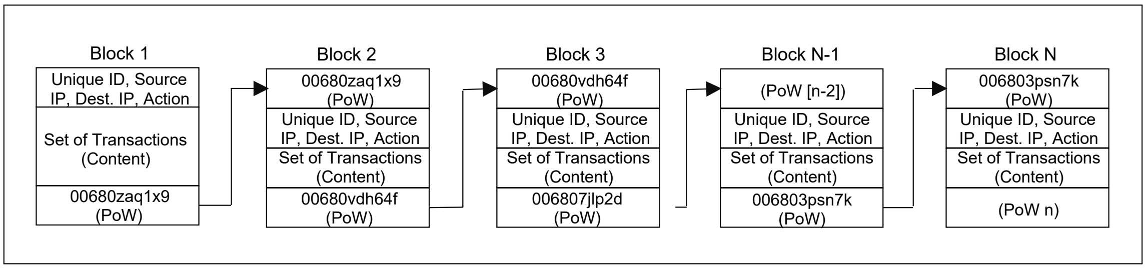


Figure 1.8: Blocks in a Blockchain

1.4.5 Consensus Mechanisms

Consensus mechanisms, used to verify transactional data between the nodes in a network. The types of consensus mechanisms used in blockchain are shown in Table 1.1.

- **Consistency, Availability and Partition tolerance (CAP) Theorem**: It defines three identity features for a distributed network. *Consistency* highlights that each participating node contains the latest information at all times. *Availability* says that a client should get a reliable response at all times. *Partition tolerance* suggests that a node should work continuously even after a network failure.

- **Byzantine Fault Tolerance (BFT)**: An agreement protocol which helps to tolerate the Byzantine failures in a network. BFT maintains the reliable record of transactions in a transparent and tamper-proof way.

- **Practical Byzantine Fault Tolerance (PBFT)**: This consensus mechanism is used when BFT fails to tolerate the faults in the network system.

- **Proof-of-Work (PoW)**: PoW is the original consensus mechanism used to verify the transactions and produce new blocks in the blockchain.

- **Proof-of-Stake (PoS)**: Defined as the consensus mechanism in which the person who acts as a validator or forger can verify the transactions. The validator or forger is selected according to the number of coins it has. In 2017, Ethereum began the process of switching from a PoW mechanism to a PoS system.

- **Delegated Proof-of-Stake (DPoS)**: This is a fast, efficient, flexible and most decentralized consensus mechanism. DPoS holds the power of stakeholder for the approval of voting and resolving the consensus issues in an honest and representative way.

- **Proof-of-Activity (PoA)**: It is the integration of PoW and PoS. This mechanism is used to verify the genuineness of all the transactions performed in the network system.

- **Proof-of-Publication (PoP)**: It is used in Bitcoin technologies to check whether particular information has published at a certain time and date or not.

- **Proof-of-Burn (PoB)**: An alternative consensus protocol for PoS and PoW. In PoB mechanism, the miners prove that they burn one cryptocurrency to create another currency, i.e., they are sent to a bitcoin address which is unsupendable.

- **Proof-of-Retrievability (PoR)**: A consensus protocol wherein a server proves that a target file is fully downloaded and retrieved by a client itself from the server.

- **Proof-of-Elapsed Time (PoET)**: A protocol that protects a network system from high resource utilization and energy consumption, thereby making it efficient.

- **Proof-of-Capacity (PoC)**: The most eco-friendly mining protocol and is popularly known as proof-of-space (PoSp) protocol. The PoC consensus protocol uses the space of the mining node's hard drive instead of using the mining device's computing power to mine bitcoins or take part in the transactions verification.
- **Proof-of-Ownership (PoO)**: PoO is used to track the owners of specific information at a certain time. This consensus mechanism can be used by the businesses to certify the integrity, date of publication and ownership of their creations or contracts.
- **Ripple**: This consensus algorithm handles the general byzantine problem and is used to maintain the distributed database across the network system. It is the real-time gross settlement system (RTGS) which relates to the transfer of currency and compensation networks.

1.4.6 Blockchain Platforms

To implement some proof-of-concept blockchain application, a platform, say using a smart contract, is required. This platform provides different rules and regulations to run an application. Most blockchain platforms support open access, are used in various applications according to their network type, supported language, and governance – see Table 1.2. The various types of blockchain platforms are explained as below.

- **Ethereum** is an open-source and distributed blockchain-based platform suggested by Vitalk Buterin, a Russian-Canadian programmer. This platform is used to run smart contracts based on the customer's specifications. Ethereum virtual machine (EVM) provides a run-time environment to smart contracts in ethereum. It is used to understand for the public (permissionless) blockchain platform and based on the PoW consensus mechanism which is slow in speed. A developer who builds an application using ethereum should pay charges in *Ether*, to execute transactions and to run an application on the network. This platform is launched by ethereum developers and contributed by ethereum enterprise alliance (EEA)
- **Hyperledger Fabric** is one of the projects of hyperledger that is designed for building blockchain-based applications and solutions. It basically uses as a modular architecture that allows network designers to alliance their important components such as- membership services, agreement, and differentiate it from other blockchain solutions. It is used to understand private blockchain networks in which only known identities can participate in a system.
- **Hyperledger Sawtooth** is an enterprise-grade used for designing to create, deploy, and execute the blockchain-based distributed ledgers that maintain the digital records. It is

Table 1.1: Consensus Mechanisms used in Blockchain

Consensus Mechanism	**Node Identity**	**Data Model**	**Language**	**Execution Environment**	**Energy Efficient**	**Processing Time**	**Resource Consumption**	**Cost**	**Throughput**	**Cons**
CAP Theorem	Private	Key-value	SQL, Python, Java, Golang	SQL, NoSQL	yes	fast	high bandwidth, CPU	high	high	high complexity, expensive
BFT	Private	Key-value	Any language	-	yes	fast	high CPU	low	high	semi-trusted, complex with more nodes, less scalable
PBFT	Private	Key-value	Golang, Java	Docker tool	yes	fast	high bandwidth	low	high	communication overhead is high for large nodes
PoW	Public	Transaction-based, Account-based	Golang, C++, Solidity, Lisp Like Language (LLL)	Native, Ethereum Virtual Machine (EVM)	no (high power)	slow	high CPU	high	low	less secure, high power consumption
PoS	Public	Account-based	Michelson	Native	yes	fast	low	medium	low	consensus control to highest paid stakeholhers
DPoS	Public	Transaction-based, Account-based	–	Native	yes	fast (faster than PoS)	low	low	high	limited token holders
PoA	Public	Account-based	Solidity, Java, Python	EVM, Docker	no (but better than PoW)	medium	high	high	high	scalablity and security is less
PoP	Private	Transaction-based, Account-based	Golang, C++, Solidity, Serpent, LLL	Native, EVM	yes	fast	low	low	high	only used to check file publications
PoB	Public	Transaction and account-based	Golang, C++, Solidity, Serpent, LLL	Native, EVM	no	medium	medium	medium	medium	costly for individual node, waste unncessary resources
PoR	Public	Transaction and account-based	Golang, C++, Solidity, Serpent, LLL	Native, EVM	yes	fast	low	low	medium	limited nodes usuage
PoET	Public	Key-value	Python	Native	yes	medium	high	low	medium	works only on dedicated hardware security
PoC	Public	Key-value	-	-	yes	slow	high memory	high	high	chances of malicious vulnerable to mining tasks
PoO	Public, Private	Account-based	Any	C#	yes	fast	medium	high	medium	expensive consensus
Ripple	Public	Account-based	Java, Go, C++	Node.js, Narcissistic Piano Mover app	yes	fast	medium	low	medium	no limitations of transactions, no incentives for nodes as it is pre-mined

used to understand private blockchain networks and based on the Proof-of-Elapsed Time (PoET) consensus mechanism to integrate hardware security solutions.

- **Hederer Hashgraph** is a new type of light, secure, fast, and fair platform that does not need the high computing power of the PoW consensus algorithm. The hederer hashgraph council is the governing body and the terms made in this platform ensures no single member or no small groups can have control and influence over the entire project.

- **Ripple** was discovered in 2012 and is aimed at connecting financial services like digital assets exchanges, banks through the blockchain network called RippleNet. It also allows global payments like Ether or Bitcoin via a digital asset called ripple.

- **Quorum** platform was founded by J.P. Morgan. As similar to ethereum, it is an open-source and free to use in endurance. It is used for private blockchain networks and would not be open for everyone. It uses a vote-based consensus mechanism that enables to handle hundreds of transactions per second. It can handle the application requiring high throughput and high speed of the transaction.

- **Hyperledger Iroha** is hosted by Linux Foundation and is used to build secure, fast, and trusted decentralized applications. This project is developed by the simultaneously working of both companies such as-National bank of Cambodia and Soramistu Cooperation Limited.

- **R3.Corda** is an open-source platform developed in 2015. It is a cutting edge blockchain platform that enables financial institutions to transact with a smart contract directly. It does not have any cryptocurrency and is used for private blockchain networks that allows only authorized participants to access data.

- **EOS** was founded by a private "Block.One" company in June 2018 and is used as an open-source platform. It was launched for designing and development of decentralized applications. The goal of this platform is to provide decentralized storage, applications, and run smart contracts. It is free for all users who want to take advantage of decentralized applications.

- **OpenChain** was developed by Coinprism and is used as an open-source platform. It is used for those organizations who manages the digital assets and needs scalability and security. It is based on partitioned consensus where one instance will have one authority to validate the transaction.

- **Stellar** is a distributed ledger technology that deals with exchanges of cryptocurrencies like Ripple. It is used to build banking tools, smart devices, and mobile wallets. It is based on stellar consensus protocol used to record financial transactions. The steller protocol has better capabilities than PoW and PoS in terms of entry for a new participant in financial services.

- **Dragonchain**, used as a service-oriented blockchain platform that provides important resources to developers and enterprises at the time of application development. It was developed at Walt Disney company in 2014 and used as an open-source in 2016. It is used for both the blockchain networks such as- public and private.

- **NEO** platform was founded by Da Hongfei (CEO) and Erik Zhang of blockchain Research and Development (R&D) company "OnChain" in Shangai. It was developed to design decentralized applications and generate GAS tokens using NEO tokens during the payment of transaction fees.

- **MultiChain** is a free and open-source platform used to build and deploy DLT-based applications instantly. It can support any programming language that provides better performance and scalability in comparison to other protocols. Therefore, the users do not require to learn a new programming language.

- **IOTA** is an open and scalable distributed ledger that has to be designed for supporting frictionless data and value transfer. It is the first distributed ledger built for the "Internet of Everything" - a network for exchanging value and data between humans and machines with tamper-proof, feeless microtransactions, and low resource requirements.

1.5 Scope of the Blockchain

Blockchain, a relatively recent technological trend, is a decentralized and chain of cryptographic blocks linked together to form a P2P network which is distributed in nature. This technology can be leveraged to achieve authorization, accountability, authentication (AAA), integrity, security, privacy, confidentiality and non-repudiation for real-time applications which may not be provided by the centralized systems effectively and efficiently.

It is a technology which is the combination of three technologies- public-key cryptography, P2P network, and the program. It has shown its revolution in terms of digital cryptocurrency that removes the requirement of an intermediatory expert in the field of registration and distribution. It has also provided the most popular product, *i.e.,* Bitcoin which is a type of cryptocurrency and work as a public ledger for all the transactions done on the network. It has resolved the problems like double-spending, unauthorized accessing, *etc.* and thus improves the security and privacy of the network. An incredible scope of this technology has been observed in various application like smart grid, voting system, financial system, supply chain management, *etc.* Incorporating blockchain with digital transactions gives many benefits such as- time and money can be saved which is used for validating and processing the transactions. Its function

Table 1.2: Blockchain Platforms

Platforms	**Focus of Industry**	**Type of Ledger**	**Consensus Algorithm**	**Use of Smart Contract**	**Governance**
Ethereum	Cross-industry	Public	Proof-of-Work	Yes	Ethereum developers
Hyperledger Fabric	Cross-industry	Private	Pluggable Framework	Yes	Linux Foundation
Hyperledger Sawtooth	Cross-industry	Private	Pluggable Framework	Yes	Linux Foundation
Hedera Hashgraph	Cross-industry	Private	Asynchronous Byzantine Fault Tolerance	Yes	Hedera Hashgraph Council
Ripple	Financial Services	Private	Probabilistic Voting	No	Ripple Labs
Quorum	Cross-industry	Private	Majority Voting	No	Ethereum developers and JP Morgan chase
Hyperledger Iroha	Cross-industry	Private	Chain-based Byzantine Fault Tolerance	Yes	Linux Foundation
Corda	Cross-industry	Private	Asynchronous Byzantine Fault Tolerance	Yes	Hedera Hashgraph Council
EOS	Cross-industry	Private	Delegated Proof-of-Stake	Yes	EOSIO Core Arbitration Forum (ECAF)
OpenChain	Digital Asset Management	Private	Partitioned Consensus	Yes	Linux Foundation
Stellar	Financial Services	Both Public and Private	Stellar Consensus Protocol	Yes	Stellar Development Foundation
Dragonchain	Cross-industry	Public, Private and Hybrid	Context-based verification with five levels of consensus	Yes	Dragonchain Foundation
NEO	Smart Economy	Private	Delegated Byzantine Fault Tolerance	Yes	NEO holders and NEO Foundation Support
MultiChain	Digital Asset Management	Private	Probabilistic Voting	Yes	MultiChain Developers
IOTA	Digital Asset Management	Public	Proof-of-Work	Yes	IOTA Foundation

on a distributed database makes the operation smoothly, ensuring tight security, and made it safe from the cyber attacks. It is one of the most consistent technologies when it requires to keep track of the digital properties. It also has the abilities to add distinct features like security and privacy in the company's structure.
The future scope of the blockchain technology in different sectors are described as under.

1. **Blockchain in digital advertising:** Presently, digital advertising faces a lot of problems like fraud domain, lack of transparency, data tampering, *etc.* Due to the issues, incentives are not affiliated but blockchain has provided a solution to ensure transparent, tamper-proof data to the network as it executes trust in a trustless environment.

2. **Cyber security:** The blockchain data is stored in the public ledgers which is verified and encrypted using cryptographic primitives. So, the data and information cannot to be tampered or attacked without any involvement of central authority.

3. **No single point of failure:** It is a decentralized technology in which each node is connected to every node without any involvement of the third party which may act as a single

point of failure. It provides a public ledger that consists of verifiable and validated transaction data which lowers the risk of data modification and trust issues on the network.

4. **Supply chain management:** It record all the information or data into the public distributed ledgers and supervise them more transparently. It also helps to minimize human errors and time delays. It is also used to monitor costs, employment, and releases at each point of the supply chain.
5. **Beyond the world of computing:** Currently, most of the countries are developing their blockchain strategies for usage in the future. But still, there are many issues such as-security and privacy in various sectors like finance where blockchain can be used to address various problems like data modification. It can also be used to generate a database for medical purpose, to manage insurance policies, *etc.*
6. **Internet of Things and networking:** The different companies like IBM, Samsung, *etc.* are utilizing blockchain technology to create a new distributed network of IoT devices. It will improve the requirement of central authority to manage the central database among all communicating parties.
7. **Cloud Storage:** Data stored on the central cloud storage can be exposed to hacking, loss of data or human error. With this technology, it is possible to make cloud storage more protected and robust against various type of attacks.

1.6 Thesis Organization

The thesis would be organized as given below along with a brief description of what the chapter would represent.

Chapter 1: Introduction
This chapter introduces the basics of centralized and distributed systems used for smart communities. Here, we briefly describe the background and history of blockchain, consensus mechanisms, and open-source platforms used in blockchain. We also discuss the scope of blockchain technology in the smart community. Moreover, the challenges associated with the distributed systems are also listed.

Chapter 2: Literature Review
This chapter details the comprehensive literature review on energy trading in smart grid systems. We propose a comprehensive background regarding the main concepts of energy trading and the implication of enabling technologies that manage the energy imbalances in the smart grid. Then, we present a problem taxonomy based on incentive, mathematical, and simulation model driven approaches, which are widely used to control and maintain the energy trading

mechanisms. Based on the findings from the literature, we also present a solution taxonomy with enabling technologies such as- Energy Internet, SDN, and blockchain. Moreover, the relative comparison of existing approaches is also given in this chapter to analyze the relative advantages and disadvantages using various evaluation parameters.

Chapter 3: P2P Energy Trading Scheduling Scheme For Electric Vehicles in Smart Grid Systems
In this chapter, the energy trading problem is formulated between the electric vehicles (EVs) and the service providers (SPs) in smart grid systems. For incentive-based energy trading between EVs and the SPs, a P2P energy trading scheduling scheme (PETS) using blockchain technology is designed. Then to solve this problem, the Stackelberg game theory-based 1-leader multiple-followers scheme is proposed that depict the interactions between EVs and the SP. Moreover, as per the announced energy price by the leader, EVs manage energy consumption by minimizing their energy bills. On the leader's side, we use the Genetic algorithm to maximize its profit.

Chapter 4: Demand Response Management Scheme for EVs in Smart Grid Systems
In this chapter, to stabilize the smart grid and to manage and control the ever-growing energy demands from EVs, we formulated the energy trading problem as non-linear that maximizes the social welfare between the EVs and the SPs. Then to solve the problem of demand response, a double auction algorithm is designed between EVs and the SPs in V2G environments. A consortium blockchain-based framework is designed to ensure secure energy transactions between them without any involvement of trusted third-party. Moreover, the energy pricing and the amount of traded energy problems for demand response are solved by auction mechanisms that maximize social welfare.

Chapter 5: Conclusion and Future Scope
This chapter concludes the thesis by highlighting the contributions made using the proposed schemes. Moreover, this chapter provides future research directions for energy trading in smart grid systems using a distributed technology.

1.7 Summary

This chapter discusses the centralized and distributed systems used for smart communities. Then, we briefly describe the background and history of blockchain, consensus mechanisms used in blockchain, and open-source platforms used for blockchain. We also discuss the scope of blockchain technology in smart communities. In the end, we discuss the various challenges blockchain technology faces in smart communities. The research work focused on energy management in smart grid systems. An incentive-based energy trading scheme and demand response management using blockchain are proposed in smart grid systems to control and audit energy consumption between EVs and the SPs. This task has been accomplished in the research work with two different approaches, game theory and auction theory, described in the following chapters. In the next chapter, we will discuss the literature survey on energy management in smart grid systems.

Chapter 2

Literature Review

IoT is an integral part of the smart grid systems, which improves the power grid system by giving timely and efficient information to the stakeholders [24, 25]. With the help of IoT-enabled technologies, the different phases of the smart grid,, *i.e.,* energy generation, distribution, transmission, and consumption, are interconnected via the *Internet* in the communication network [26]. Hence, the smart grid facilitates bidirectional energy flow between prosumers and consumers by integrating power generation, transmission, distribution, and utilization systems.

V2G is an emerging technology in the smart grid system that supports energy exchange between prosumers and consumers, where energy management plays a vital role in balancing the demand and supply of energy between them [27]. Energy management includes various types of mechanisms such as- energy trading, demand response, and dynamic pricing. Among all of these mechanisms, energy trading is one of the most effective mechanisms, which accounts for the concern of both the supply and the demand sides. In this mechanism, the prosumers aim to provide electricity to consumers and adhere to the physical constraints of the power grid [28]. They can schedule with the generators for generating energy as per the demand of energy by the end-users [29,30]. On the other side, consumers reshape their demands according to the supply conditions. The energy demand from the consumers is the function of unit price that influences the supply strategies of the prosumers. The participation of prosumers and consumers in the wholesale market is accepted as the inevitable solution to enhance the economic efficiency of energy markets, reduce peak demand and price volatility, and improve the reliability of electric power systems. From the past few years, various demand response programs have been promoted by power system operators to encourage the active involvement of end-users. Moreover, these programs can provide system services to the end-users at electricity markets. The demand response requirements in energy markets, such as- the minimum curtailment level, could curtail eligible customers or leave off potential small customers from participating in demand response programs. The demand response aggregation is acknowledged as an efficient solution to increase the exposure of large volumes of consumers to energy markets. In this way, demand response aggregators work with the customers to give appropriate offers that would allow customers to participate in an energy market. These aggregators work with load-serving entities to provide customers with advanced metering data that monitors and control of real-time energy consumption in an energy market [31]. For automation of energy consumption, there are several models, *i.e.,* simulation, incentive, and mathematical used in energy trading that provides great potential to the participants by optimizing the energy cost and energy consumption in the smart grid. Among all these models, incentive models such as- price theory, bargain theory, game theory, auction theory, and contract theory, are most commonly used for energy trading in smart grid systems. But, to frame an energy trading mechanism, game theory is one of the most popular and economic tools to analyse and maintain the rational interaction between two or more individuals in the energy market. With these mechanisms, optimization, linear programming, Markov decision process (MDP), genetic algorithm, reinforcement learning, *etc.* are also used, which improves the energy consumption and find the right behaviour of energy trading participants.

Figure 2.1 shows the architecture of the smart grid system that includes renewable energy resources (RERs), smart transportation, power technologies (investigate all aspects of electric power generation and distribution with significance on sustainable technology and environmentally sensitive issues), and widespread EVs. With this, many new technologies have been introduced into smart grid systems such as- micro-grids (smart building with wind generators, solar panels *etc.* and trade energy in a P2P manner, V2G networks (EVs acted as energy storage devices [32]. They can sell their energy to the power grid as well as other vehicles in a P2P

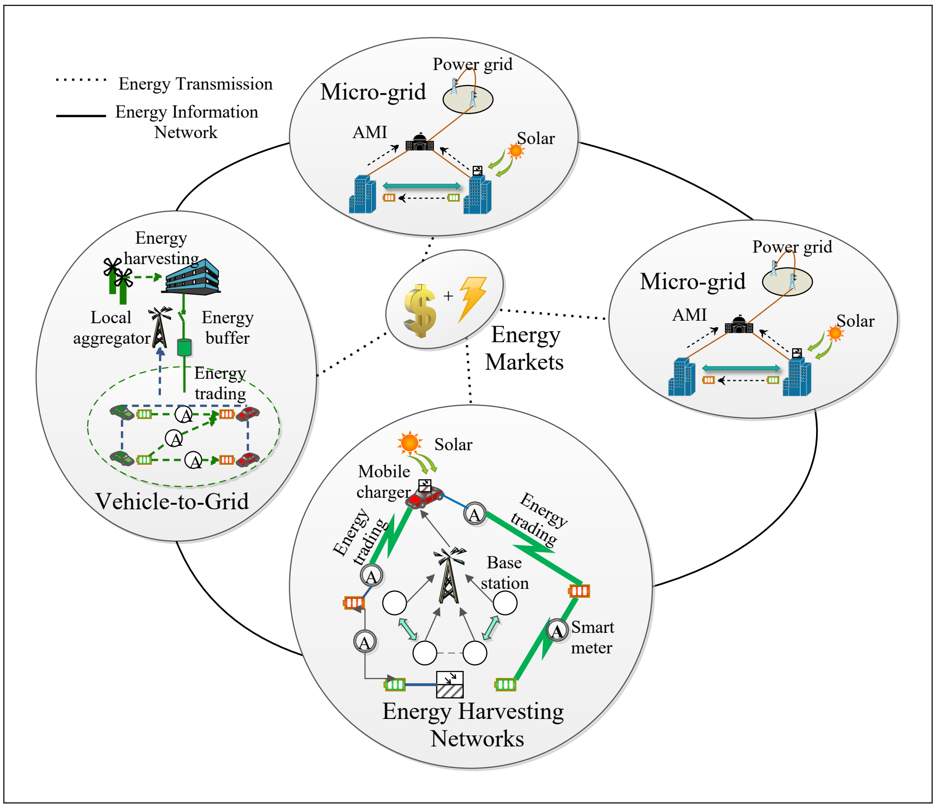


Figure 2.1: Conceptual view of the smart grid

manner using local aggregator and reduce peak loads), and energy harvesting networks (with this ability, the nodes can charge their battery from renewable energy/ mobile charger in a P2P way [33]). Moreover, the smart grid systems develop an efficient and green P2P energy trading by reducing the amount of energy wasted and improving efficiency of generation, delivery and consumption. [34]. Taking all the characteristics and features of energy management in the smart grid system, the energy trading mechanisms become more complicated. So, there is a big challenge in smart grid systems to improve the social welfare of energy transactions or energy exchanges between prosumers and consumers that makes the energy trading system more reliable.

2.0.1 Analytical Reviews to the existing literature

Many research articles have been published on energy trading that manages the smart grid's energy demand and supply. For example, Bayram *et al.* [35] provided an overview of distributed energy trading concepts in smart grid systems. They have presented the enabling technologies, which are required to communicate with trading companies. Similarly, Zhang *et al.* [36] discussed the incentive-based approaches adopted in energy trading control mechanisms. In the same way, Zhou *et al.* [37] discussed the existing agent-based simulation models used for electricity markets. Pierluigi Siano [38] proposed demand response potentials and benefits in the smart grid, facilitating the coordination of efficiency in smart grid systems. Wang *et al.* [39] provided a comprehensive survey on communication architectures used in power grid systems, which are responsible for delivering electricity and energy-related information to the end-users. Pagani *et al.* [40] presented a survey on different power grid infrastructure using complex network analysis based technologies and methodologies. Abdella *et al.* [41] presented a literature review of on-demand response optimization models, power routing devices, and power routing algorithms, used in P2P energy trading. Similarly, Tushar *et al.* [42] provided a comprehensive review on P2P energy trading using blockchain. They have identified various challenges that address the virtual and physical layers of energy trading with the existing research. In the same way, Zhou *et al.* [43] proposed a comprehensive survey on P2P energy trading based on an academic paper, research papers, and industrial projects.

From the analytical reviews of the literature, we observed that no research article had been published that describes all the energy trading approaches and optimization models, which are used for energy trading mechanism in smart grid systems. Hence, there is a need to investigate the various approaches and methods used for energy trading mechanism in smart grid systems. In this chapter, we present the energy requirements and challenges of energy trading mechanism. We also review the existing approaches used for energy trading in smart grid systems, and provide a relative comparison of the state-of-the-art approaches. Table 2.1 shows the comparative analysis of the proposed survey with the existing surveys.

Table 2.1: Comparative analysis of the proposed survey with the existing surveys

Reference	**Contribution**	**Taxonomy available**	**Comparative analysis with existing approaches using tables**	**Incentive models**	**Mathematical models**	**Simulation models**	**Enabling technologies: SDN, Energy Internet, Blockchain**
[35]	Provided an overview on distributed energy trading concepts	×	×	✓	×	×	✓
[36]	Provided a comprehensive review on incentive-based approaches used in energy trading	×	✓	✓	×	×	only Blockchain
[37]	Agent-based simulatin models used in electricity markets	×	×	×	×	×	×
[38]	Presented a survey on demand response and smart grid	×	✓	×	×	×	×
[39]	Comprehensive review on communication architectures used for power systems in the smart grid	×	×	×	×	×	×
[40]	Presented a survey on power grid systems	×	✓	×	×	×	×
[41]	Presented a survey on P2P distributed energy trading in the smart grid	✓	×	×	×	×	✓
[42]	Provided a comprehensive review on P2P energy trading	×	✓	✓	×	✓	only Blockchain
[43]	Provided a comprehensive review on P2P energy trading	×	×	✓	×	×	only Blockchain
Our work	Presented a survey on energy trading in the smart grid	✓	✓	✓	✓	✓	✓

2.1 Energy trading in Smart Grid: A Problem Taxonomy

In this section, we discuss and review existing approaches used for energy trading in the smart grid based on incentive models [44] [45], simulation models, and mathematical models. The detailed view of these models is described in the following sections. Figure 2.2 shows the representation of problem taxonomy used for energy trading in smart grid systems.

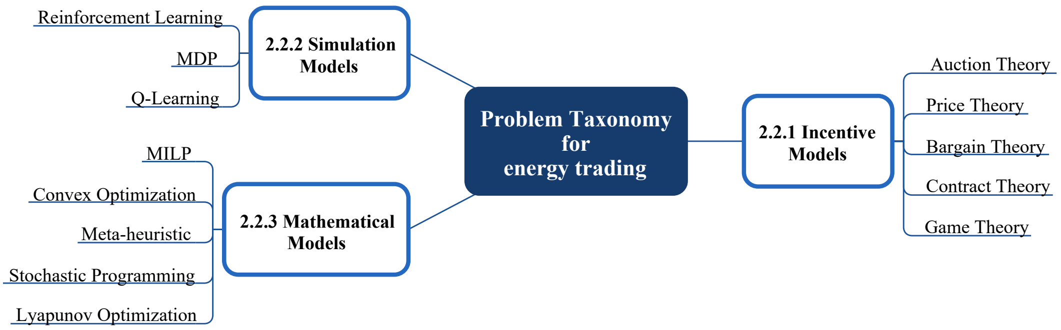


Figure 2.2: Energy trading in the smart grid: A Problem Taxonomy

2.1.1 Incentive models

In this section, we presented some theoretical issues based on incentive economic approaches. It mainly focuses on dynamic pricing, game theory, bargain theory, auction theory, and contract theory.

2.1.1.1 Auction Theory

Auction is a mechanism used in the energy market to trade energy between sellers and buyers, which improves their utilities by purchasing the goods. The first-price sealed-bid auction, descending-bid auction, ascending-bid auction, and the second-price sealed-bid auction are the four types of auction mechanisms [46]. The result of an auction is the amount of the final price of the goods used for trading. In an auction theory, several auctioneers value the goods by evaluation criteria for sale. This evaluation information is secret and private from one another. But there is unsymmetrical or unbalanced energy information in the auction process in which selfish auctioneers may change their true valuations by bidding the good untruthfully. This may harm the efficiency and truthfulness of the trade. In this context, Zhong *et al.* [47] proposed a Vickrey-Clarke-Grove auction mechanism to solve energy trading in a multi-energy system. This mechanism ensures three economic properties like truthfulness, economic efficiency, and individual rationality. Similarly, in [48], the authors proposed two auction mechanisms for two-layered V2G architecture that also ensures economic properties. In the same way, the authors in [49] proposed a V2G auction mechanism and analytic target cascading framework for the multiple micro-grids and distribution network to provide economic properties with social cost minimization. For instance, to buy the same amount of electricity, the grid or power utility can earn a high price during peak timings when the energy demand is more as compared to the off-peak timings. So, to improve the efficiency of electricity distribution, there is a need for autonomous and distributed energy management. In this context, the distributed auction scheme based on blockchain is suitable between local users and small-scale energy givers for autonomous management. With the help of this scheme, the private information of the participants is shared only among local nodes to improve privacy and security, energy-efficiency and cost-efficiency of V2G network in the smart grid [50]. On the other hand, to consider the integrity and privacy of the smart grid, adaptive hierarchical auction-based energy trading schemes are important and play a major role for energy management. Due to increasing demands and limited capacity of the energy generation resources, one consumer may purchase or sell energy from the number of energy providers, where a multi-item energy auction scheme is required. Thus, using auction schemes in energy trading, the risk of lack of RERs and the fluctuations produced in generation of energy from RERs should be taken into consideration.

2.1.1.2 Price Theory

It is a powerful approach for customers to act in an economically optimal manner. According to the demand for electricity, the smart grid load varies with time, which is analogous to electricity prices at different times. In this order, the pricing schemes can be categorized into three types [51], which are described as follows.

- **Real-Time Pricing (RTP):** It is generally the hourly rate that applies to customers on the usage of electricity on an hourly basis. This pricing is time-varying as per the current conditions of energy demand and must be informed to customers accurately and timely. So, it is the most useful type to improve the efficiency and efficacy of the energy markets [52].
- **Time of Use (ToU) Pricing:** This pricing is released in advance and unlike RTP, it is constant for a long period of time. It does not change with day-to-day changes in the energy market. It can reduce the overall costs for both the utility and customers.
- **Inclining Block Rate (IBR) Pricing:** It is designed for customers where prices are recognized based on electricity consumption levels. It charges a high rate per kWh at higher energy usage levels and a lower rate at lower usage levels. The average electricity consumption determines these levels in a period with the fixed thresholds.

In this context, some researchers have used pricing theory to the manage energy trading efficiently. For example, Wu *et al.* [53] proposed a smart micro-grid model based on pricing theory by local energy traders. This model has benefits for customers as well as for producers from energy trading. They have used the two-layered optimization algorithms in which a bottom-layer optimization describes the energy trading decisions by customers and producers according to the price announced. In contrast, a top-layer optimization describes the gain of local energy traders with the benefits of energy consumers and providers. Similarly, Morstyn *et al.* [54] developed a strategy based on marginal pricing that manages and controls the uncertainty with energy prices and local energy trading between the producers and the customers. In the same way, the authors in [55] used the RTP scheme to satisfy the consumers and optimize the energy benefits of producers. The relationship between the demanded loads and the pricing scheme is defined as follows.

$$L = \beta . P^{el} \tag{2.1}$$

whereas, L represents the demanded loads, el is the price elasticity, P is the electricity price, and β is a constant. In this order, the pricing theory also has been used to balance the load via two-way energy flow between EVs and the smart grid. This theory solves the amount and time of the exchange of energy between them in the V2G system [56].

2.1.1.3 Bargain Theory

It can be defined as a negotiation process during meetings between the workers and the employees to reach an agreement or to improve pay and conditions in the power electricity markets [57]. In the bargaining theory, the consumers can tackle energy consumption for their preferred payment in the smart grid. Unlike auction theory, which focuses on maximizing the utility function of bidders and auctioneers, bargain theory concentrates to achieve a fair and self-executing agreement.

For a specific bargaining solution, it is usual to follow Nash's proposal. The solution should satisfy frequent axioms like efficiency, symmetry, scalar invariance, monotonicity, *etc*. So, the Nash bargaining solution is the unique solution of a classical bargaining problem, which satisfies the theory of scale invariance, symmetry, Pareto optimality, and independence of irrelevant alternatives. It maximizes the product of an agent's utilities on the bargaining set and many researchers follow the Nash equilibrium to solve the bargaining problem [58]. For example, Kim *et al.* [59] proposed a two-phase approach for addressing the nonconvexity of generalized Nash Bargaining among multiple micro-grids for direct energy trading. The first phase solves the optimal power flow problem, and the second phase determines the market price clearance. Their evaluation results show that they have reduced the network cost. For bargaining among the N number of players, the Nash bargaining problem can be defined as follows.

$$\begin{aligned} max \prod_{n \in N} (U_i^c - U_i^d) \\ \{B_n^*\}\ s.t. (U_i^c \geq U_i^d), \forall i \in N \end{aligned} \tag{2.2}$$

where U_i^c and U_i^d are the utilities of player i gained with and without collaboration respectively, and B_n^* is the Nash equilibrium solution with constraint of utility of the player gained with collaboration is greater than the utility of the player gained without collaboration.

The energy trading process in the smart grid includes several participants such as EVs, producers, consumers, and a different types of electric devices. Taking all these participants into a centralized bargaining process will increase the complexity of distributing bidding goods and bidding costs among collaborators. So, distributed bargaining process can be scalable and efficient solution with limited information exchange. In this context, Wang *et al.* [60] proposed a Nash bargaining theory to strengthen and fair benefit in energy trading. They developed a decentralized solution with minimum information exchange overhead in energy trading. Their numerical results show the reduction of total cost of the interconnected micro-grids operation and an individual participating micro-grid achieved by 29.4% reduction in its cost through energy trading [61].

2.1.1.4 Contract Theory

According to the features and characteristics such as energy generation and energy consumption in energy trading, there are various types of participants. Commonly, each participant delivers the best trading scheme to earn more profit or reward. Moreover, due to asymmetric information (where one side participants are not aware of the other side) in energy trading, the problem may be intensified. So, to address this problem in energy trading, contract theory can be a viable solution that incentivizes the participants under asymmetric information [62].

Considering N number of participants in energy trading having each participant has its type (a_i, b_i) where $i \in N, N = 1,2,3,...,N$. Here a_i is the reward for i^{th} participant to trade b_i amount of electricity.

For designing feasible contracts, it should satisfy the individual rationality and incentive compatibility constraints that are defined as under.

- **Individual Rationality:** A contract satisfies this constraint when the utility (U_i) of each type of participants must be non-negative, which is as follows.

  $$U_i(a_i,b_i) \geq 0, i \in N \tag{2.3}$$

  This constraint motivates the trading where profit can be gained by self-interested participants.

- **Incentive Compatibility:** A contract satisfies this constraint when the contract of i^{th} participant attain the highest utility U_i they could obtain as follows.

  $$U_i(a_i,b_i) \geq U_j(a_j,b_j), i,j \in N, i \neq j \tag{2.4}$$

So, a well-planned contract mechanism is utilized to maximize the benefit in energy trading. For example, Amin *et al.* [63] proposed a scheme to categorize energy suppliers for energy trading between electricity suppliers and an aggregator. They developed an optimal contract-based scheme that allows energy suppliers to sell their energy at different prices. Their energy prices are based on the cost of the production of unit that maximize the benefits of total cost to the aggregator. Their numerical results show the effectiveness of contract theory in energy trading. Similarly, Zhang *et al.* [64] proposed a contract-based direct energy trading model for energy buyers and sellers having uncertainty in the generation of renewable energy resources. In the same way, the authors in [65] proposed a cloudlet-based vehicle-to-vehicle energy trading system. This system has been modeled by contract theory. The energy switch center purchases electricity from discharging vehicles and then resells it to the charging vehicles without transmission of energy on the grid. Their simulation results show that the proposed model increases the profit of energy switch centers compared to the other mechanisms.

2.1.1.5 Game Theory

This theory can be defined as where producers (suppliers) and consumers (demanding users) are participating in the local energy market of the smart grid. The change in one party can affect the strategies of other party. So, to balance and analyze the energy trading strategies, game theory can be a viable solution.

In a game theory, the main three components are set of players as N, its action as A_i, and its corresponding utility function U_i, where i represents the number of players N. In this theory, each player chooses its A_i to maximize the U_i. The utility function of one player does not depend only on its action but also depends on the other player's actions other than i. In a normal-form game (N, A, U), the expected utility U_i for player i of the mixed-strategy profile $s_j = (s_1, ..., s_n)$ is defined as follows.

$$U_i(s) = \sum_{a \in A} U_i(a) \prod_{j=1}^{n} s_j a_j \tag{2.5}$$

The main aim of the game players is to minimize and optimize the utility function by controlling the strategies like mid value, nash equilibrium, mid value+1, *etc.* From all the strategies, the most important one for game theory is known as the Nash equilibrium. In this strategy, a player cannot retrieve additional profits from changing actions or we can say that the other players remain consistent in the game strategies. According to the players, the game theory is classified into two types such as cooperative game and non-cooperative game. In non-cooperative games, individual players can compete with each other, whereas in cooperative games, the player can play only for self-enforcing. This theory can be used to detect suspicious activities via intrusion detection system in vehicular networks [66].

In this order, non-cooperative games are suitable for P2P energy trading between the prosumers and the consumers. Instead, cooperative games are suitable for improving social welfare in energy trading with the help of a communication network. Several research articles have been published on energy trading in the smart grid using game theory. For example, El Rahi *et al.* [67] proposed a game to maintain price uncertainty in prosumer-centric energy trading. They formulated a single-leader, multiple-follower Stackelberg game where the power company acts as a leader that declares its price strategy for maximum profits. Prosumers act as followers who choose the optimal energy bid. Latifi *et al.* [68] proposed a solution for energy management and energy trading in the smart grid. They described the solution in three phases, *i.e.,* (i) a game-theory based energy management model with reinforcement learning to schedule the power consumptions in micro/nano-grids, (ii) an incentive-based double auction mechanism for directly trading in micro/nano-grids, and (iii) an optimal power allocation program that reduces transmission loss and destructive effects of power in energy trading. Park *et al.* [69] designed an energy trading mechanism based on a contribution energy allocation scheme in the smart grid. A distributor distributes its energy to customers based on their contribution level, whereas customers receive this energy to maximize their utility. They have formulated the problem using non-cooperative game theory with the existence and uniqueness of the Nash equilibrium. Tushar *et al.* [70] proposed a cake cutting game that discriminates price technique and ensures envy-free energy trading. In this game, energy users set the price per unit of energy to sell surplus energy and study fairness criteria to attain maximum benefits. Their results show that the game possesses a socially optimal called Pareto optimal solution. The authors proposed a Stackelberg game model in event-driven energy trading in micro-grids. This model provides an optimal bidding algorithm for retailers. Their simulation results show that this model has linearithmic complexity with acceptable expandability and applicable in time-varying cases [71]. Similarly, the authors in [72] proposed a game-theoretic approach for solving energy trading, which allows consumers to minimize the energy bill and producers to make a profit from their excess of energy. In the same way, Alsalloum *et al.* [73] proposed a game theory that frames the different interactions (different prices for the buyers) between the prosumers and the smart grid.

EVs are one of the prominent solutions for the sustainability issues needing critical attention like global warming, depleting fossil fuel reserves, and greenhouse gas emissions. They can also act as a storage system, to mitigate the challenges associated with renewable energy sources and to provide the grid with ancillary services, such as voltage regulation, frequency regulation, spinning reserve, *etc*. For extracting maximum benefits from EVs and minimizing the associated impact on the distribution network, optimal integration of EVs has been done. Mohammad *et al.* [74] proposed a literature on the modelling of grid-connected EV-PV (photovoltaic) systems. They presented a comprehensive review of modelling a grid-connected EV-PV system via, control architectures, charging algorithms, and uncertainty analysis. With this, EVs are various advantages like environmentally friendly, low noise production *etc.* to use EVs in the smart grid. But, some problems, such as energy consumption by EVs, are unstable and unpredictable [75]. However, EVs are sensitive to the decisions taken by their owners, which specifies their charging/discharging rates and the payments. For example, the authors in [76] proposed a both models, such as demand response management and energy trading for EVs in an off-grid system. The hierarchical decision-making scheme of this model has been analyzed as a single-leader-heterogeneous multi-follower Stackelberg game. Their simulation results show that the transaction price decreases in the proposed market model as compared to an existing energy market models. Similarly, the authors in [77] discussed the network topology of energy trading for EVs in the smart grid, which has been considered as a multi-leader multi-follower Stackelberg game. Hence, by designing optimal game theories, EVs are accelerated to provide additional assistance to the V2G network and help to meet the service demand of the smart grid.

From the above-mentioned incentive-based approaches, we observed that game theory is one of the most popular and widely used techniques for energy trading in the smart grid. It optimizes the utility function that captures the tradeoff between economic benefits and related costs, such as reducing battery life, storage efficiency, *etc.* in energy trading.

2.1.2 Simulation Models

The simulation model-based study is used to exemplary the management and performance of multiple type of models at different scale of decision-making processes in the smart grid. These multiple models are the use of statistical learning algorithms such as reinforcement learning [78], Q-learning [79], so that energy traders can acquire long-term policies based on profit standards in an autonomous way [80, 81].

2.1.2.1 Reinforcement Learning

It is an area of machine learning in which the products depend on the present input state and the next computation of product depends on the previous product output. In this learning, the output decision is dependent on the parameters that has been decided for the production [82]. Initially, reinforcement learning has been used for video and strategy board games but recently used for optimizing the storage of energy and generation of energy from RERs in the smart grid [83–85]. The optimal energy trading approach depends on the dynamic demand-supply and time-varying energy prices in the grid. Hence, it is very difficult for the grid to acquire such information in time [86, 87]. So, many researchers have used reinforcement learning that impacts the grid's future battery level and trading policies. For example, Chen *et al.* [88] described the learning module based on deep reinforcement learning in a holistic market model design. The local energy market in the smart grid facilitates short-term and prompt energy exchanges [71]. The DSO or distribution network operator (DNO) is used for the regulation of energy markets in the smart grid having reinforcement learning. The utility providers provide energy not only to customers but also attempt several retail plans for long-term policies. Meantime, energy producers also develop their energy exchange approaches having several energy devices such as batteries and distributed energy resources. A local energy exchange can be satisfied by the advantage of the present distribution line and smart meters for billing and payment [89]. The authors in [90] developed a model for energy trading in the smart grid having reinforcement learning. This model optimizes the micro-grid battery level, estimation of energy generation from renewable energy resources, and the current demand of electricity in the smart grid. However, its performance degenerates at the large-scale of the smart grid with strict energy demand estimation error and latency [91]. To enhance the energy trading in the micro-grids, the authors have compared the deep reinforcement learning-based algorithms such as Proximal policies optimal (PPO) and Deep deterministic policy gradients (DDPG) [92]. Zhang *et al.* [93] proposed a deep reinforcement learning-based double auction energy trading scheme to maximize the benefits of all agents, *i.e.,* buyers and sellers. Their simulation results show that profits has increased for sellers and cost has decreased for buyers. Similarly, Lu *et al.* [94] proposed a deep reinforcement learning model for energy trading to solve the demand-supply mismatch problem and to optimize the battery level of the grid. Their simulation results based on the smart grid with *three* micro-grids each equipped with wind turbines show that this scheme increases the micro-grid utility compared to the existing schemes. Shateri *et al.* [95] proposed a deep reinforcement learning algorithm named deep double Q-learning to manage the privacy cost in smart meters during energy trading in the smart grid. Wang *et al.* [96] proposed an energy trading model based on the repeated game in which each micro-grid chooses its approach individually and randomly for trading and maximize its revenue. They have used two learning automation algorithms based on reinforcement learning that protects the grid's private strategy. Similarly, Peters *et al.* [97] used autonomous broker agents with reinforcement learning between sellers and buyers, which can operate in smart electricity markets and ensure profit-maximization and long-term energy trading policies. In the same way, the authors in [98] used broker agents modeled with MDP and Q-learning techniques.

Q-Learning is a classic form of reinforcement learning that uses Q-values (also known as action values). These action values improve the performance and efficiency of learning agent iteratively. This learning algorithm helps to make long-term trading policies for traders independently. For example, the authors in [89] proposed an indirect user-to-user energy trading model in a localized event-driven market. They utilized reinforcement learning techniques built on MDP with a modified Q-learning to benefit all market participants. Furthermore, the work discussed by the authors in [99] proposed simulation-based modelling for local energy trading.

As per the discussion and existing proposals on simulation models, we observed that there is a need for more research on simulation models so that energy trading mechanisms utilize the deep reinforcement learning adequately and efficiently in the smart grid.

2.1.3 Mathematical Models

As time passes, there is an exponential increase in energy demand [100]. If this energy demand is not controlled and coordinated by equivalent energy response then there is a cause of peak hour load that leads to frequency deviation from normal values. This whole deviation destroys the energy trading system. So, various techniques must be executed by utility companies to assuage energy demand and control this balance. The strategy can either be used RERs for trading during off-peak timings to control and assuage the high energy demands or to handle the power grid units to generate high amount of energy that completes the demand of trading. However, this may result in high maintenance and operational costs and reduce performance because of underutilization. In this case, mathematical models are capable to find an optimal energy load to be traded. By the mathematical models like mixed-integer linear programming (MILP) [101], convex optimization [102], particle swarm optimization (PSO) [103], Lyapunov optimization [104], many researchers described the energy trading in the smart grid. These optimization techniques help study the effects of different components in energy trading and make predictions about behavior [105]. For example, Alam *et al.* [106] proposed an energy cost optimization algorithm to minimize the total cost of energy trading. Their simulation results show that 99% of solutions provided by this optimization algorithm are optimal ones. Lin *et al.* [107] established a model based on MILP to optimize the decision of a single end-user, which further decides the charge/discharge of the energy storage and the EVs on the Internet of Energy. Similarly, Zhong *et al.* [108] used the MILP for non-convex-based social welfare maximization and energy trading problems between the buyers and the sellers in a cooperative energy market. Alam *et al.* [109] addressed the residential energy cost optimization problem in the smart grid. The authors break down the mixed-integer non-linear programming (MINLP) problem having NP-hard complexity into multiple MILP modules and solve these modules iteratively. They have maintained the Pareto optimality so that no households are worse-off to improve the cost of others. In this paper [110], authors presented a distributed convex optimization technique for energy trading among various micro-grids. Their main aim is to minimize the total operational cost of the system by optimal exchange of energy by the micro-grids. Their simulation results show that the cost minimization algorithm proved convergence over non-connected micro-grids. Similarly, the authors in [111] proposed a centralized and distributed solution for energy trading between two micro-grids. The central controller has accessed all the information, whereas a distributed approach solved a local optimization problem iteratively. They have used a convex optimization technique, which minimizes the transportation cost of energy exchange and total cost of the energy generation. Ramachandran *et al.* [112] employed a PSO scheme to minimize the cost of energy generation for realistic energy market prices, distributed generator bids chasing operational costs, and load bids as per consumers' priorities. They have used an auction process for the trading strategy. Their simulation results indicate that the viability and efficiency of the proposed system reduce the cost of energy by 37% as compared to the conventional method reduces only up to 35%. With this, Pattanaik *et al.* used the K-means clustering model to find the shortest distance in vehicular roads [113]. This model can helps in energy trading to find an optimal for EVs.

In an another case, the energy generation from RERs and stochastic optimization methods used that addresses the ambiguity, mistrust, and uncertainty in energy generation. In this context, the authors presented a model in [114] where they proposed a profit maximization problem from consumers standpoint using stochastic programming. Similarly, Do Prado and Qiao [115] proposed a decision-making energy trading scheme between the customers and energy retailers. The authors have considered the stochastic native of demand response participation of customers, which is solved by MILP. Hu *et al.* [116] proposed an energy management scheme in a micro-grid with multiple conventional generators, renewable generators, and energy storage systems. They have presented a robust two-stage optimization approach using Lyapunov optimization, which meets quality-of-service (QoS) to handle large difficulties in the load demands and renewable energy generation, and provides an efficient solution under limited computational resources.

From the facts discussed in mathematical models, we found that optimization techniques used in energy trading mechanisms are highly useful. Further, these techniques optimizing energy consumption and energy transmission cost. Table 2.2 shows the detailed summary of the existing proposals mentioned in the problem taxonomy of energy trading in the smart grid.

2.2 Solution Taxonomy for energy trading: Enabling Technologies

This section discusses three enabling technologies for future energy trading in the smart grid, such as- SDN, Energy Internet, and blockchain. These technologies are used in energy trading mechanisms because the traditional power system is highly dependent on a central authority, leading to a single failure point. Also, there is a chance of destruction of the participants' private information, which causes security and privacy issues in energy trading. So, to resolve and address these issues, we explore the energy trading mechanisms in terms of enabling technologies. The detailed view of these technologies is described as follows. Figure 2.3 shows the representation of solution taxonomy for energy trading in smart grid systems.

Figure 2.3: Solution taxonomy for energy trading in the smart grid

2.2.1 Software-defined Networking-based Energy Trading in Smart Grid Systems

Power routers play an important role in energy trading, which provides various key functionalities such as bi-directional energy flow, energy conversion *i.e.* kinetic energy to electrical energy and vice-versa, routing, and transmission scheduling. It is one of the core elements of the Energy Internet that provides bidirectional communication and two-way energy flow. For adequate, efficient, and effective management of power routers, there is a need for an influential routing, coordination, and powerful communication that are essential between routers to achieve global stability. In this context, many researchers have proposed a SDN architecture as a possible solution for managing the network infrastructure in smart grid [118–122]. Unlike traditional networking systems, SDN allows the rules of centralized control system and follows the dynamic configuration of network devices. We observed from the literature survey

Table 2.2: Detailed summary of the existing proposals described in the problem taxonomy

Reference	**Model**	**Type and No. of traders supported by Model**	**Privacy Consideration**	**Consideration of RERs**	**Consideration of EVs**	**Energy-efficient**	**Cost-efficient by means of energy production + transportation cost**
[47]	Vickrey-Clarke-Grove auction mechanism	Manager and user within multi-energy district. Fulfilled three essentials truthfulness, individual rationality, economic efficiency	×	×	×	✓	✓
[48]	Auction mechanism	1000 households within smart grid. Fulfilled three essentials truthfulness, individual rationality, economic efficiency	×	×	✓	✓	✓(Social cost)
[49]	Auction mechanism	Multiple Micro-grids. Fulfilled three essentials truthfulness, individual rationality, economic efficiency	×	×	✓	✓	✓(Social cost)
[53]	Price theory	Local prosumeras nad consumers	×	×	×	×	✓(Energy trading cost)
[54]	Price theory	Prosumer-to-Prosumer	×	✓	×	✓	✓(Energy trading cost)
[55]	Price theory	Any number of traders	×	×	×	✓	✓(Energy trading real-time pricing)
[59]	Bargain theory	4 Micro-grids	✓	✓	×	✓	✓
[60]	Bargain theory	Among Micro-grids	×	✓	×	✓	✓
[61]	Bargain theory	Among Micro-grids	×	✓	×	✓	✓
[63]	Contract theory	Multiple electricity suppliers and single aggregator	×	✓	×	✓	✓
[64]	Contract theory	One electricity consumer and 80 small-scale electricity suppliers	×	✓	×	✓	✓
[65]	Contract theory	Multiple electric vehicles and one energy switch center	×	✓	✓	✓	✓(maximum profit to energy switch center)
[67]	Stackelberg Game theory	Multiple Prosumer and Single Consumer	×	×	×	✓	✓
[68]	Stackelberg game theory + reinforcement learning + double auction	10 Micro-grids each having 100 appliances randomly chosen between low/mid/high-flexible appliances	×	✓	✓	✓	✓(transmission cost)
[69]	non-cooperative game theory	Local Consumers	×	×	×	✓	×
[70]	cake-cutting game theory	Any number of energy users	✓	×	×	✓	✓(energy trading cost)
[71]	Stackelberg game theory	7 no. of providers	×	×	×	✓	×
[72]	Game theory	Multiple buyers and sellers	✓	✓	×	✓	✓(energy cost)
[73]	Game theory	Buyer and seller	×	✓	×	✓	✓(energy cost)
[76]	Stackelberg Game theory	8-10 electric vehicle's users	×	✓	✓	✓	✓(energy cost)
[77]	Stackelberg Game theory	5000 electric vehicles and 4 micro-grids	×	✓	✓	✓	✓(energy generation cost)
[88]	Deep reinforcement learning model	Multiple electric vehicles and one energy switch center	×	✓	×	✓	×
[90]	Game theory + Deep reinforcement learning model	Multiple micro-grids	×	✓	×	✓	×
[89]	Reinforcement learning model + Markov decision process	Customers and Prosumers	×	✓	×	✓	✓
[91]	Energy management model	30 users within micro-grid	✓	✓	×	✓	✓(Communication cost)
[92]	PPO and DDPG	3 villages Northern Kordufan State, Hamza ELsheikh, Tannah, and Um Bader	×	✓	×	✓	✓

Reference	Model	Type and No. of traders supported by Model	Privacy Consideration	Consideration of RERs	Consideration of EVs	Energy-efficient	Cost-efficient by means of energy production + transportation cost
[93]	Double Auction, Deep Reinforcement Learning	10,000 training episodes with each has 24 training steps	×	×	×	×	✓
[94]	Deep reinforcement learning	Three micro-grids	×	✓	×	✓	×
[95]	Deep reinforcement learning, Q-learning algorithm, Deep double Q-learning	Data set	✓	✓	×	✓	✓
[96]	Reinforcement learning model + Stackelberg game theory	Among micro-grids	✓	×	×	×	×
[97]	Reinforcement learning model	Broker agents	×	×	×	✓	×
[98]	Reinforcement learning model + Markov decision process	Broker agents	×	×	×	✓	×
[99]	Simulation model	Agent-based simulation	×	×	×	✓	✓
[106]	Bi-linear optimization model	Datasets collected in Ottawa Canada [117]	×	✓	✓	✓	✓
[107]	Mathematical mixed-integer linear programming model	Energy storage and electric vehicle of an individual	×	✓	✓	✓	×
[108]	MILP-Based Nash Bargaining Solution	15-node network with 2 sellers and 13 buyers	×	✓	×	✓	✓
[109]	Mixed-integer linear programming model	Tesla Model 3 2017 and Tesla Powerwall 2	×	✓	✓	✓	✓
[110]	Convex optimization model	"M" no. of multiple micro-grids	✓	✓	×	✓	✓
[111]	Convex optimization model	Two micro-grids	×	✓	×	✓	✓
[112]	Particle swarm optimization	Local prosumer and consumer	×	✓	×	✓	✓
[114]	Stochastic programming	end-users (homes, buildings, and communities)	×	✓	×	✓	✓
[115]	Stochastic optimization	PJM historical data	×	✓	×	✓	✓
[116]	Lyapunov optimization	Multiple micro-grids	×	✓	×	✓	✓

that SDN-based networking had been used in the existing smart grid systems for better efficiency and achieves better QoS. For example, the authors in [123] suggested an SDN-based networking architecture for digital grids routers in which control, data, and energy planes are separated. The control plane is referred to as a part of a centralized software controller. There are software-defined data and energy controllers used for data and energy flow control in this plane, respectively. In the data plane, various data types have been generated and transmitted. In contrast, in the energy plane, distributed renewable resources and energy storage are deployed at the user side and P2P energy trading can also done.

From the aforementioned facts, we believed that a SDN-based communication network could provide improved energy scheduling and energy optimization. Moreover, novel and efficient routing algorithms should developed to improve energy trading performance and quality in the smart grid system. Figure 2.4 shows the proposed SDN-based architecture used for energy trading in the smart grid. This architecture has three planes include control plane, data and energy plane, and infrastructure plane. It provides a better solution to energy trading to control and manage the data and energy in the smart grid. Thus, an essential feature of this architecture is the separation of the control, data, and energy planes. The technologies in the three planes, such as controllers, network devices, and grid devices, can be developed independently. These devices can communicate with each other by open interfaces and makes the infrastructure more flexible and energy-efficient. The control plane is used to manage the data dynamically and energy plane with their respective controllers. This plane achieves programmability and flexible cooperation between data and energy plane. The data plane is responsible for providing energy-related data services, while the energy plane is responsible for physical energy flow control. The infrastructure plane is referred to as a layer of users. The bottom layer of Figure 2.4 shows the three scenarios, such as micro-grid, V2G, and energy harvesting networks, which are used for energy trading in the smart grid.

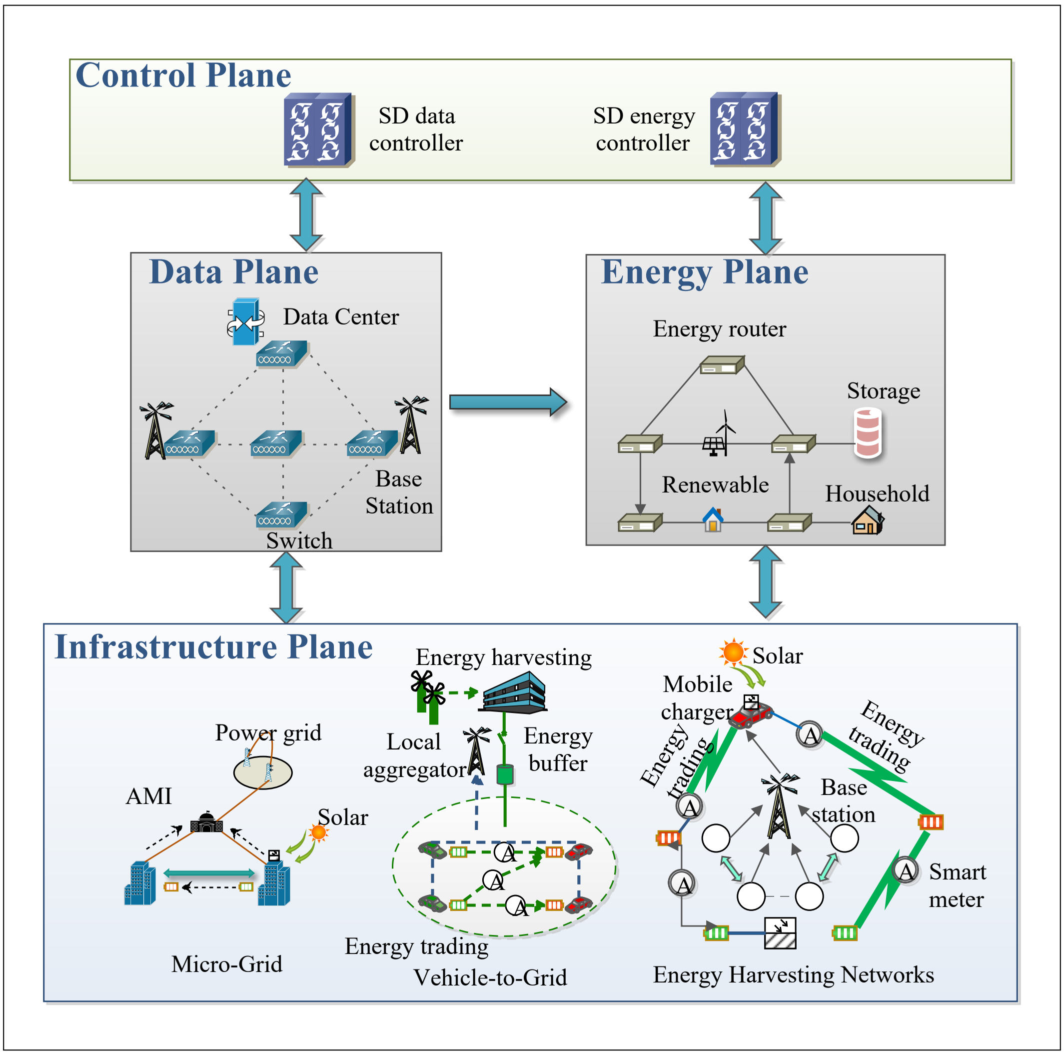


Figure 2.4: SDN-based energy trading architecture in the smart grid

2.2.2 Internet of Energy-based Energy Trading in Smart Grid Systems

Today's energy trading of the smart grid accommodates only power energy. However, energy can be generated from renewable and non-renewable energy resources such as chemical, thermal, and electromagnetic. From the study, we observed that the next generation will not only limited to electrical energy for energy exchanges but will incorporate all energy resources. The new and latest power systems are being created from this interconnection, which is known as Energy Internet [124]. It is anticipated as the Internet of energy networks, which aggregates all energy resources in an open inter-connection similar to the Internet. It is the the combination of information technology (IT), power and electronics technology (PET), and smart management technology, and a large number of power networks, which are composed of distributed energy storage devices and various types of loads. Moreover, it provides flexible energy scheduling, bidirectional energy flow, and power conversions from one energy to other in the smart grid [125]. So, it is one of the promising technologies for P2P energy trading, and its consequences have been discussed in [126, 127]. According to the [128], Energy Internet solves a peak load shifting method in energy trading. The authors provided a P2P energy trading framework to end-users to trade the stored energy in their respective distributed energy storage facilities. Similarly, Lin *et al.* [129] proposed a energy sharing between the houses of the smart grid via Energy Internet. Their simulation results show that after sharing the energy, each house make a high profit in one day as compared to the existing energy sharing methods.

However, Energy Internet is developing technology that has not been consistent and standardized in the real world. Its concepts and methods have not yet been fixed, which makes it an interesting area for future investigation. But, energy trading based on the Internet-of-Energy (IoE) can encourage end-users to develop and store renewable energies to address energy issues (electricity demand) in the smart grid.

2.2.3 Blockchain-based Energy Trading in Smart Grid Systems

A big limitation in an existing V2G network is the lack of privacy and security of the energy transactions between consumers and prosumers [130]. The conventional energy trading architecture in the smart grid leads to high operating costs, high maintenance cost with low performance and productivity [41]. In an another way, a P2P energy trading architecture having blockchain offers a distributed platform that provides secure energy exchanges [131, 132]. In the traditional energy sector, due to high amounts of carbon emissions produced by the high carbon intensity of combustion of fossil fuels, which leads to air pollution and irreversible effects of climate change. Facing these environmental issues, on one hand, facilitate distributed RERs to be integrated into distribution systems for carbon mitigation and transmission efficiency. On the other hand, the authors have formulated a carbon pricing scheme using blockchain to charge carbon producers for allowances to phase out the power plants with extremely high carbon intensities. [133]. Blockchain is an emerging technology, which ensures immutability, security, privacy, tamper-proof payment transactions in an energy trading of the smart grid [22, 134] [135]. It allows verification, P2P file-sharing system, and the public storage of information in a distributed manner [136]. It prevents the information from being changed or manipulated and provides verifiable of historical events and user anonymity without the involvement of central authority [23, 137]. The identity privacy and authentication of energy transactions are higher in a distributed platform instead of traditional platform [138,139]. Also, this technology promotes electronic contracts named smart contracts between the energy prosumers and the energy consumers [140–143]. Moreover, it also supports the energy trading between the EVs that dynamically enter and leave the network in the smart grid system. These characteristics make the blockchain a viable solution to serve the distributed energy exchange market. In this context, Saxena *et al.* [144] proposed a blockchain-based P2P energy trading scheme that reduces peak demand and smart home electricity bills. Their simulation results show that peak demand reduces with weekly savings in a Canadian micro-grid using the Hyperledger platform. Having the same platform, the authors in [145] demonstrated a P2P energy trading and energy sharing model having blockchain that reduces energy consumption at peak hours [146]. In a same way, Jamil *et al.* [147] proposed an energy model based on blockchain having Hyperledger Fabric network between the prosumers and the consumers to aggregate the information for monitoring real-time load. They have also used the data analytics technique for extracting hidden patterns and information for right decision-making and managing energy distribution. Abdella *et al.* [148] proposed Istanbul Byzantine fault tolerance (BFT) consensus having permissioned blockchain for energy trading in the smart grid. They have compared the proposed consensus with the existing ones such as ethereum clique, Hyperledger Fabric, and proof-of-work (PoW) and show the results that the proposed consensus has 15 times low latency and double the throughput. Khorasany *et al.* [149] proposed a proof of location consensus that provides location awareness in P2P energy trading of the smart grid. Petri *et al.* [150] implemented a P2P energy trading framework to support energy clusters and study the interactions between producers and consumers in the power grid. Their simulation results show that this implementation reduces the fluctuation in energy exchanges and costs. Similarly, Khalid *et al.* [151] implemented a hybrid P2P energy trading model using blockchain that reduces cost and peak to the average rate of electricity in the smart grid. In the same way, Aggarwal *et al.* [152] proposed a blockchain model for storing and accessing the data generated by smart homes in a secure manner. The model has 3 phases: 1) selecting smart home as miner node based on power capacity, 2) a block creation and validation, and 3) transaction handling for secure energy trading. Their evaluation results show that *EnergyChain* model performs better in terms of communication cost and computation time than the existing models. Wang *et al.* [153] proposed a minimum cut maximum flow theory to schedule distributed energy sources. They have used blockchain to record the information and management of power energy trading. Their simulation results show that the proposed system is cost-efficient for power energy consumption than the existing ones.

With this, game theory has been widely used for designing and analyzing energy systems. In this context, many researchers have used dynamic programming to maximize the benefits for trading participants [154] while others have used the incentive models and game theory for the purpose and framework of P2P energy trading in the smart grid [155]. These P2P energy trading models reduce the burden of electricity on a centralized power system to balance the load on the peak demand period [156, 157] and increases the profit of energy market participants [158,159]. In addition, Esmat *et al.* [160] used the ant colony optimization with auction in a blockchain-based energy trading to provide fast trading settlements, security, and high level of automation. The main aim of blockchain-based energy trading is to inspire and strengthen the energy trading users to trade energy with one another so that the charging rates of central power stations may not affect the productivity and efficiency of the P2P energy trading [42, 161]. For example, Hassija *et al.* [162] proposed a blockchain-based protocol, *i.e.,* directed acyclic graph for energy trading in V2G networks. They have used the game theory for the negotiation between the vehicles and the grid at an optimized cost [163]. Similarly, Liu *et al.* [164] proposed a non-cooperative Stackelberg game model to discuss the relationship between the sellers and the buyers in P2P energy trading. In the same way, Anoh *et al.* [165] proposed a Stackelberg game-theoretical model to secure the interactions between producers and the consumers in a virtual micro-grid. Their simulation results show that their trading model gives higher benefits to the trading participants than the other existing game models. Ullah *et al.* [166] proposed a two-tier clearing market model in a distributed P2P energy trading of smart grid that improves the economic benefits than conventional single-tier market model. Similarly, Elkazaz *et al.* [167] proposed a decentralized-based and hierarchal P2P energy trading model for the management of energy of smart homes. They have used the MILP and shows the cost reduction in annual household energy management system. Chen *et al.* [168] proposed an incentive-based game theory model to secure energy trading between the EVs. To provide consistency in the data blocks, they have used a practical byzantine fault-tolerant (PBFT) mechanism that increases transaction throughput and reduces transmission delay. Their simulation results show that this model saves 64.55% communication overhead as compared to the existing models. In addition, Zhou *et al.* [169] proposed a blockchain-based secure energy trading for information asymmetry. They have used the contract theory and solves the optimization problem by the convex-concave algorithm. Their evaluation results show that the proposed model has achieved a high successful probability in block creation for energy trading transactions. Morstyn *et al.* [170] developed a bilateral contract networks between energy generators and consumers. Their network ensures scalability and price adjustment among traders.

Some researchers have used the P2P energy trading model to solve security and privacy problems in energy trading. In this context, the authors in [171] used the state channel-based energy trading that increases the throughput of blockchain and solves security and privacy problems in the smart grid. Similarly, Lu *et al.* [172] proposed a blockchain-based renewable energy trading model to provide security and privacy in the smart grid. Their evaluation results proved that the model gives high operational efficiency and low computational overhead. In a same way, Guan *et al.* [173] proposed an efficient secure and privacy-based energy trading scheme. They have used the attribute-based encryption with blockchain technology having credibility-based equity proof mechanism. Mezquita *et al.* [174] developed a smart contract on the Ethereum platform for blockchain-based energy trading in a micro-grid. This model provides security to the traders and ensures minimal energy cost and profitable energy production. In the same way, Gai *et al.* [175] solved the problem of privacy leakage in P2P energy trading using blockchain. Yi *et al.* [176] proposed a homomorphic encryption scheme for blockchain-based energy trading that provides privacy-preservation to the electric vehicles in the smart grid. Kang *et al.* [177] proposed a localized P2P electricity trading system with consortium blockchain method to achieve trust and secure electricity trading. They have used the auction mechanism to optimize electricity pricing and traded electricity among Plug-in hybrid electric vehicles (PHEVs). Similarly, Muzumdar *et al.* [178] proposed a Vickrey auction for blockchain-based P2P energy trading that ensures trustworthy, average throughput, and average cost-efficient. They have used the proof-of-stake (PoS) consensus having ethereum platform to aggregate the information of energy trading in the smart grid. In an another work, Hassan *et al.* [179] developed a differentially private energy auction for the blockchain-based micro-grid system, which modifies the Vickrey–Clarke–Groves auction mechanism. Their auction mechanism performs better in terms of cost, security, and privacy. It outperforms the traditional mechanisms to maintain the profit of overall network and social welfare and also maximizing the sellers' fund. Doan *et al.* [180] proposed a double auction mechanism for energy trading scheme in the smart grid. They have used the blockchain technology and maximizes the profit of all participants who are participated in the network and to achieve social welfare. Similarly, Guerrero *et al.* [181] proposed a P2P energy trading model based on continuous double auction and stable matching algorithm to find the shortest path between the agents. Their evaluation results show that the proposed system reduces the losses and line congestion in the energy markets. In the same way, Bandara *et al.* [182] proposed a flocking-based double auction in a decentralized P2P energy trading. Their trading model shows that they have 80% successful trading simulation results within neighbourhoods. In addition, Gomes *et al.* [183] proved by a case study that auction-based P2P energy trading decreases the energy costs without the need for load shifting consumption optimization or the acquisition of new equipment.

There exists a finite number of articles based on distributed P2P energy trading having blockchain [184]. However, it is a new technology and their integration with smart grid is not yet examined and analyzed to its full potential. Moreover, in many countries, blockchain-based standards and regulations do not recognize for P2P energy markets in the smart grid [185]. Hence, proper energy rules and standard need to be modified and explored before the implementation of P2P energy markets. In this context, Lu *et al.* [186] have discussed the blockchain technology in SDN-based distributed energy trading scheme in the Energy Internet. First, in a distributed Energy Internet architecture, the sheer volume of data makes it difficult for centralized systems to meet demand. Second, the security and privacy-preserving of distributed systems are difficult to solve. So, the authors have used RERs for energy generation, blockchain technology for protecting the privacy of energy transactions, and SDN has been applied to operate, control, and manage all parts of the system model. Similarly, Chaudhary *et al.* [187] proposed an SDN in secure energy trading using blockchain in the smart transportation system. The distributed secure system used to authenticate, audit,verify, and validate the EVs participating in the network. Qian *et al.* [188] proposed a secure and efficient scheme for data aggregation in the smart grid. The authors have used homomorphic encryption that reduces the computation cost and resist quantum attacks on the data. It also provides security, data privacy and data integrity on the aggregated data in the smart grid. Similarly, Chen *et al.* [189] discussed the security, privacy, and anonymity in exchanges of energy flows and financial activity in the smart grid using blockchain implementation. Liu *et al.* [190] proposed a blockchain-based renewable energy incentive-based power trading mechanism in the smart grid. This framework provides security to the participants and improves the efficiency of power trading and renewable energy consumption. With security and privacy of the agents, the privacy-preservation of smart meter data in the smart grid is also a major concern [191]. For example, Shen *et al.* [192] presented a privacy-preserving two-level random permutation method adequately and securely between massive meter data and their sources in the smart grid. Similarly, Mohammadali *et al.* [193] presented a privacy-preserving homomorphic scheme with multiple dimensions and fault tolerance for metering data aggregation in the smart grid. In the same way, Sanduleac *et al.* [194] Proposed a framework for knowledge extraction from high reporting rate smart meters data to enhance the grid monitoring services with privacy-preservation of the user.

By gaining the knowledge from literature review, we designed a P2P energy trading architecture using blockchain technology as shown in Figure 2.5. In this architecture, the energy coins are transferred from an energy buyer's wallet address to the energy seller's wallet address after the energy exchanges between them. The memory pool of energy aggregators (EAG) has latest energy blockchain data for verifying the payment transaction. The new transaction records generated by the energy buyers are uploaded to EAGs for auditing, which are further verified and digitally identified by the energy sellers. Therefore to obtain the proper balance between demand and supply on a blockchain energy, we implement incentives that reassure energy nodes to fulfil the energy demands out of self-interest. As per the duration of an energy trading, the energy seller is rewarded with energy coins with the contribution of energy exchanges between the energy sellers and the buyers. The PoW consensus mechanism is used on a blockchain to verify and validate the energy transactions between the energy sellers and buyers.

Table 2.3 shows the detailed summary of existing proposals mentioned in the solution taxonomy of energy trading inthe smart grid. It includes various parameters such as technology, type and No. of traders supported by the model, privacy and security, consideration of EVs, consideration of RERs, and cost-efficient energy production and transportation cost, which describes the difference among various existing proposals having enabling technologies.

Table 2.3: Detailed summary of the existing proposals described in the solution taxonomy

Reference	**Technology**	**Model**	**Type and No. of traders supported by Model**	**Privacy and Security**	**Consideration of EVs**	**Consideration of RERs**	**Cost-efficient by means of energy production + transportation cost**
[123]	SDN-Centralized	SDN approach	Three groups of energy service providers customers	×	✓	✓	✓(energy generation, storage and transmission cost)
[128]	Energy Internet-Decentralized	Mathematical programming model	Smart energy building and smart polygenic micro-grid	×	×	✓	✓(energy cost)
[129]	Energy Internet	Hybrid approach with harmony search	-	×	×	×	✓
[131]	Blockchain-Decentralized	-	Consumers and Distribution system Operator-Ethereum implementation	×	×	×	×
[133]	Blockchain-Decentralized	Pay-to-public hash with multiple signatures	Number of 7 prosumers	✓	×	✓	✓
[144]	Permissioned Blockchain-Decentralized	Auction mechanism	4 smart homes within Canadian Kontright Centre Micro-grid	✓	✓	✓	✓
[146]	Permissioned Blockchain-Decentralized	Proof-of- Energy Generation and Proof-of-Energy Consumption	Number of 5 prosumers	×	×	✓	✓(energy consumption cost)
[147]	P2P Blockchain	Predictive analysis (RNN model)	Dataset of smart grid with 1,16,189 instances	✓	×	✓	✓
[148]	Blockchain	Istanbul BFT	HyperledgerBesu with 10 validator nodes	✓	×	×	×
[149]	Blockchain-Distributed	Proof of Location mechanism	IEEE-33 bus system with 14 producers and 18 consumers	✓	×	×	✓
[150]	P2P-Decentralized	Cluster Federation	Number of energy producers and consumers	×	✓	✓	✓(energy consumption cost)
[151]	Blockchain-Decentralized	Smart Contracts on Ethereum	600 electricity prosumers and 400 consumers	✓	×	✓	✓(energy consumption cost)
[152]	Blockchain-Decentralized	EnergyChain	-	✓	×	×	✓(communication cost)
[153]	Blockchain-Distributed	Minimum Cut Maximum Flow theory	China Southern Power Grid Data	✓	×	×	✓
[154]	P2P-Decentralized	Dynamic programming + Auction mechanism	1 seller and 4 buyers within micro-grid	×	×	✓	×
[156]	P2P-Centralized	Game theory + Auction mechanism	Number of 12 prosumers	×	×	×	✓(energy production and transmission cost)
[157]	Blockchain-Decentralized	-	-	✓	×	×	✓(energy production and transmission cost)
[158]	P2P-Centralized	Non-cooperative game theory	20 photovoltaic households and 30 electric consumers	×	×	✓	✓(energy production and transmission cost)
[159]	Blockchain-Decentralized	Reverse auction mechanism	5 charging and 6 discharging electric vehicles	✓	×	✓	✓(electricity purchasing cost)
[160]	Blockchain	Ant Optimization + Auction mechanism	3 buyers & 3 sellers + feeders with 17 primary nodes with smart meter	✓	×	×	✓
[42]	Blockchain-Decentralized	Auction mechanism + Game theory	Number of sellers and buyers	×	×	✓	✓(energy production and transmission cost)

Reference	**Technology**	**Model**	**Type and No. of traders supported by Model**	**Privacy and Security**	**Consideration of EVs**	**Consideration of RERs**	**Cost-efficient by means of energy production + transportation cost**
[162]	Blockchain-Decentralized	Non-cooperative game theory	3 grids and 10 electric vehicles	×	✓	×	✓(energy selling cost)
[163]	Blockchain-Decentralized	-	-	×	✓	×	✓(electricity selling cost)
[164]	P2P-Distributed	Non-cooperative Stackelberg game theory	4 micro-grids	×	×	✓	✓(energy cost)
[165]	P2P-Distributed	Non-cooperative Stackelberg game theory	Number of 10 prosumers	×	×	✓	✓(energy cost)
[166]	P2P-Distributed	Two-tier market clearing	4 area with 9 prosumers	×	×	×	×
[167]	P2P-Decentralized	Mixed-integer Linear Programming	Data of 4 houses in community	×	×	×	✓
[168]	Blockchain-Decentralized	Elliptic curve + Game theory	2 average number of electric vehicles	✓	✓	×	×
[169]	Blockchain-Decentralized	Contract theory + Stackelberg game theory	Number of 20 electric vehicles	✓	✓	×	✓
[170]	P2P-Decentralized	Bilateral contract theory + Game theory	Micro-grid with diesel generator, an intermediate supplier and 25 prosumers	×	×	✓	✓
[171]	Blockchain-Decentralized	State channel theory	-	✓	×	×	×
[172]	Blockchain-Distributed	Credibility-based equity proof mechanism	-	✓	×	✓	×
[173]	Blockchain-Distributed	Credibility-based equity proof mechanism	-	✓	×	✓	×
[174]	Blockchain-Distributed	Multi-agent system	Negotiating between agents in the micro-grid	×	×	×	✓(energy transmission cost)
[175]	Consortium Blockchain-Decentralized	Privacy-preserving blockchain-enabled model	Multiple neighboring users in smart grid	✓	×	×	×
[176]	Blockchain	Homomorphic encryption	-	✓	✓	×	×
[177]	Energy Internet + Blockchain-Decentralized	Double auction mechanism	Real dataset: Urban area of Texas	✓	✓	×	✓(electricity pricing)
[178]	Distributed-based Blockchain	Vickrey Auction mechanism	20 consumers and 19 prosumers	✓	×	×	✓
[179]	Blockchain-Decentralized	Game theory + Auction mechanism	50-250 buyers (if 'n' buyers then, 'n-1' sellers)	✓	×	✓	✓(social welfare)
[180]	Blockchain	Double Auction-based Stackelberg	Hyperledger (chaincode) 5-22 prosumers	✓	×	✓	✓(social welfare)
[181]	P2P-Blockchain	Continous Double auction mechanism	50 prosumers and 50 consumers	✓	×	✓	✓
[182]	P2P-Decentralized	Double auction mechanism	Road network data from California state (50 houses)	×	×	✓	×
[183]	P2P-Decentralized	Auction mechanism	Weekly energy consumption of local micro-grid	×	×	×	✓(energy pricing)
[187]	Blockchain-Decentralized	SDN-approach	200 electric vehicles, 10 charging stations, and i transaction server controller	✓	✓	×	×

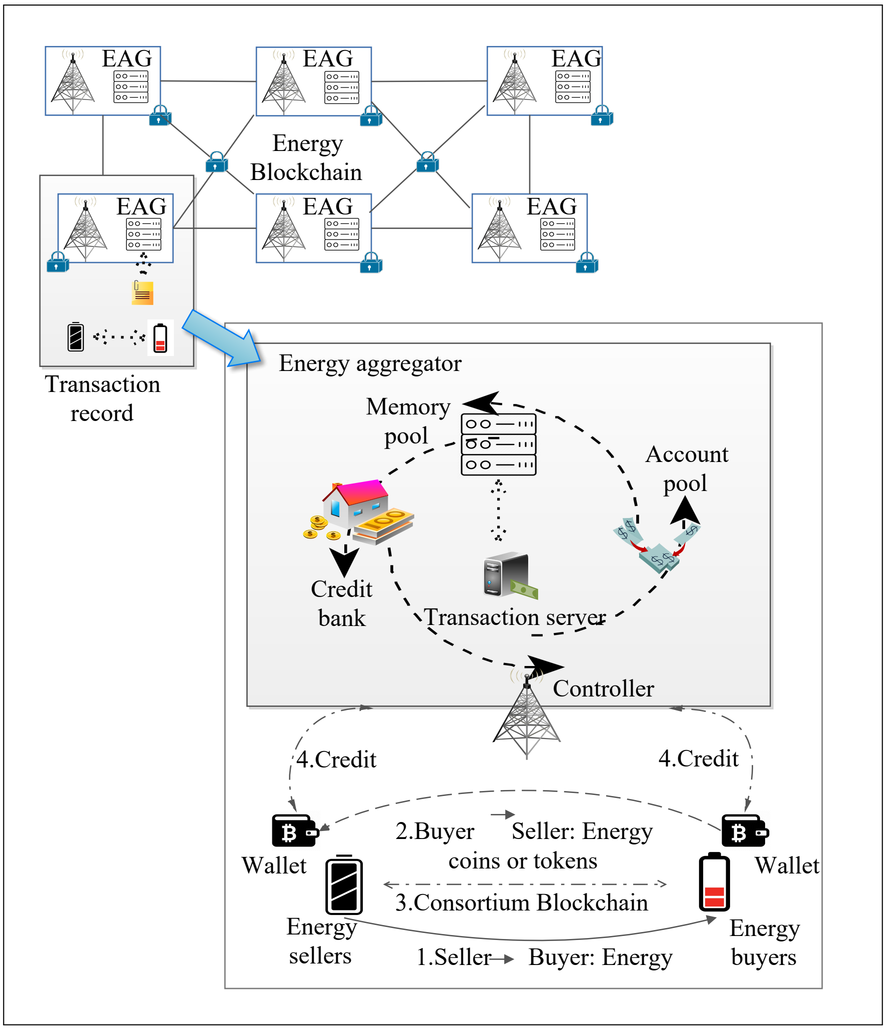


Figure 2.5: Architecture for P2P energy trading in the smart grid

2.3 Current state-of-the-art for energy trading in smart grid systems

In this section, we review the related work for P2P energy trading in smart grid systems. Many research articles proposed by the researchers for P2P energy trading into several sectors [42, 170, 195–198] such as micro-grid [199], EVs [177], and distribution networks [200].

Alam *et al.* [201] proposed a P2P energy trading model for smart homes in the smart grid. They considered the Pareto optimality to optimize and minimize the total energy cost of the system. Aznavi *et al.* [202] proposed a P2P energy trading model between EVs and the entities equipped with solar energy generation. They used the dynamic pricing mechanism to increase the owner's profit. Their simulation results show a reduction of 23.24% in the total cost of prosumers. Nguyen *et al.* [203] proposed a decentralized P2P energy trading mechanism having EV-wireless charging-discharging lanes. They described a privacy-preserving consensus protocol for desired energy price and amount of EVs. Zhang *et al.* [204] proposed joint energy trading and uncertainty in the energy market. Their simulation results balance the photovoltaic forecast error by 55.3% locally. Tushar *et al.* [205] proposed a coalition game-based P2P energy trading and mid-market rate pricing mechanism to ensure stability in the smart grid. Similarly, Tushar *et al.* [206] proposed a P2P auction mechanism for energy trading where the authors shared the storage of energy between the shared facility controllers and the community. Leong *et al.* [207] proposed a bidding strategy based on a Bayesian game to ensure fair bidding in P2P energy trading. Similarly, Faqiry *et al.* [208] proposed a double auction mechanism to protect users' private information in P2P energy trading. They optimized the social welfare problem where buyers aim to minimize their energy price and sellers aim to maximize their energy consumption. Chai *et al.* [209] proposed a Stackelberg game for P2P energy trading to maximize the participants' benefits. Similarly, Paudel *et al.* [210] proposed a Stackelberg game model to find the interaction between the utility companies and end-users to maximize the benefits of both. Zhou *et al.* [211] proposed a pricing methodology for electric vehicle chargig stations for the consumption of renewable energy. The selection of Charging stations by the EVs is based on charging price, distance and traffic congestion information. Similarly, Amini *et al.* [212] proposed a distributed consensus and innovations approach for optimal charging of plug-in EVs in transportation electrification networks. Aggarwal *et al.* proposed a demand-response management scheme for energy trading between EVs and the SPs to maximize the social welfare maximization [213].

However, despite using P2P energy trading, the above-mentioned implementations [207, 209, 210, 214] do not provide a secure platform to share data and energy among peers. Therefore, there is a possibility of leaking peers' personal information and compromising the system's reliability. To address these security problems, we propose a P2P energy trading scheduling, *i.e.,* PETS scheme using blockchain technology. It is a distributed ledger technology (DLT) where transactions are recorded securely in a decentralized way. It provides immutability, transparency, privacy, and security to smart grid systems. Once the transactions are recorded on a blockchain, there is no possibility of tampering with the transactional data secured by cryptographic primitives [215]. From these advantages, researchers have used this technology in P2P energy trading in various sectors [23] such as intelligent transportation [187, 216], vehicle-to-grid (V2G) [50, 217], smart grid [134, 218], and smart homes [152] to maintain transparency and trust in energy trading [219]. They designed the smart contracts on the Ethereum platform for defining the energy trading logic, including the auction mechanism [159, 220], game theory [162, 165, 180, 221–223], bargain theory [224], and incentive contract theory [168]. Li *et al.* used the improved krill herd algorithm to solve a mixed-integer programming-based problem between EVs and power grids in energy trading. They implemented the proposed model on Hyperledger Fabric and evaluated the scalability and performance of the model [225, 226]. An *et al.* [**?**] proposed a multi-bid online incentive scheme for energy trading in multi-microgrid systems, in which microgrids act as buyers and sellers to trade surplus energy.

From the literature study, we have observed that blockchain technology in P2P energy trading between EVs and the SPs having game theory had not been widely used. Hence, we propose

Table 2.4: Comparative analysis of PETS scheme with the existing schemes

References	**Contribution**	**Theory**	**Optimization method**	**Block-chain**	**RTP-based scheduling**	**Smart contracts**
Lasla *et al.* [220]	Blockchain-based energy trading for EVs	Auction theory	-	✓	×	✓
Liu *et al.* [159]	EVs-based power trading using blockchain	Reverse Auction theory	-	✓	×	✓
Hasija *et al.* [162]	Lightweight framework for data sharing and energy trading	Directed Acyclic Graph	-	✓	×	✓
Zhang *et al.* [221]	Energy trading on a distributed platform with transmission cost	Game theory	-	-	×	✓
Jember *et al.* [222]	Energy transmission management in Internet of EVs	Game theory	Contract theory	-	×	-
Ma *et al.* [223]	RTP scheme for energy management	Game theory	Game theory	-	✓	-
Anoh *et al.* [165]	P2P energy trading i virtual micro-grids	Game theory	Game theory	×	×	-
Doan *et al.* [180]	P2P energy trading using blockchain	Game theory	Game theory	✓	×	✓
Ping *et al.* [224]	EVs charging coordination method using blockchain	Alternating direction method of multipliers (ADMM)	Bargain theory	✓	×	-
Chen *et al.* [168]	Secure electricity trading for EVs	Game theory	Contract theory	✓	×	✓
An *et al.* [**?**]	energy trading in multi-microgrid systems	incentive compatibility	multi-bid online auction	✓	×	-

the P2P energy trading scheme between EVs and the SPs in smart grid systems. It uses real-time pricing, game theory, and blockchain to manage and optimise P2P energy trading. None of the existing proposals have addressed the real-time pricing of EVs' energy consumption in P2P energy trading. The comparative analysis of the current state-of-the-art existing schemes is described as shown in Table 2.4.

2.4 Research Gaps

After the detailed analysis of the aforementioned existing proposals, following research gaps have been identified which need further investigation.

2.4.1 Decentralized system for smart grid energy trading

- First, there is a requirement of distributed mechanism that provides security in energy trading for smart grid systems.
- Traditional mechanisms depend on a trusted third-party authenticator that manages, audits, and verifies each energy transaction. The centralized authority may be vulnerable to security attacks such as- single point of failure, DoS, and privacy leakage. For example, any middleman attackers may alter, tamper, or manipulate the transferred data.

- Existing research proposals more focus on EV charging and discharging facilities while ignoring the security and privacy issues.

- Existing solutions lack the design of incentive-based energy trading in smart grid systems. Due to the increased battery consumption, EV users are not interested in participating unless they get good rewards from energy trading while scheduling at the destination.

2.4.2 Information asymmetry

- The choice of EV users to take participate for energy trading in smart grid systems refers to their private information that is only known to the EVs. This scheme is known as information asymmetry.

- Existing proposals have pretended that every node present knows EVs' private information, which is a significant concern for EV users to take part in energy trading.

- Therefore, it is important to propose an incentive-based energy trading scheduling scheme that can effectively maximize the utilities of participants with information asymmetry preservation.

2.4.3 Decentralized Demand response management

- Existing solutions lack of mechanisms in the smart grid system for a decentralized demand response management. To create a proper balance between the demand and response during peak hours, there is a need for secure and reliable framework in smart grid systems.

- The existing smart grid frameworks for demand response management are dependent on a centralized authority which act as a single point of failure. Therefore, a distributed or decentralized based framework is required to provide a proper balance of demand response and control with respect to demands during peak hours.

- To address this challenge, we will design a smart grid framework for demand response management, which leverages blockchain technology to enable secure and efficient energy trading.

2.4.4 Load profile alteration

- The global ecosystem has witnessed an exponential growth in the number of attacks on various smart communities and applications such as- load profile alteration. To handle this situation in a network system, the dependability on cybersecurity mechanisms has also increased to a great extent.

- There exists many solutions to handle different type of cyber attacks on smart communities. However, the need of ubiquitous services in smart communities on the move creates hurdles in front of the existing security solutions for many attacks (such as- replay attack, DDoS, data modification, eavesdropping, *etc*).
- Therefore, to tackle these attacks in a distributed environment, blockchain technology can be an effective solution.

2.4.5 Existing standards and protocol pitfalls in smart grid systems

- Existing standards and protocols that have been used in the smart grid system such as- IEC/TR 62357: Service Oriented Architecture (SAO), IEC 61970: Common Information Model (CIM) / Energy Management, IEC 61850: Power Utility Automation, IEC 62351: Security, IEC 62056: Data exchange for meter reading, tariff, and load control *etc*.
- But, these aforementioned smart grid standards are based on a centralized authority which may act as a single point of failure and can lead to privacy issues. So, we will propose a decentralized based blockchain consensus protocols using consensus mechanism, *i.e.*, PoW, PoS, DPoS etc. to provide security and privacy in SG system for energy management.

2.4.6 Energy-Efficiency

- EVs communication enlarges the energy efficiency of network due to short distance communication but they have limited battery lifetime. Generally, the communication among EVs depends upon the peer discovery and communication protocols.
- Along with the security issue, it is also not possible to charge the batteries due to eavesdropping or any other type of attacks which results in high communication cost and time.
- So, to prolong the lifetime of EVs, a proper energy efficient scheme is required between the EVs and the SPs in smart grid systems.

2.5 Objectives of the Research Work

By analyzing the research gaps found in related work, following objectives are set-forth:

1. To carry an extensive literature survey on a decentralized secure energy management system.
2. To design an efficient incentive-based energy trading scheme between EVs and SPs.

3. To propose a framework for secure and decentralized demand response management scheme in smart grid systems.

4. To validate the proposed framework by using various performance evaluation metrics in different scenarios.

2.6 Summary

In this chapter, we reviewed and examined the energy trading mechanisms used in the smart grid. A discussion has been carried out on the four-layered architecture and requirements of the energy trading mechanism. Then, we reviewed a problem taxonomy on several typical models, such as incentive, mathematical, and simulation-based energy trading schemes. We mainly targeted the approved schemes in which energy trading mechanisms constitute various design challenges. Further, a solution taxonomy based on energy trading having enabling technologies has been discussed. Several unsolved issues have been extracted from the literature review on energy trading between prosumers and consumers. Then, we provide a viable solution on an extensive view of SDN, Energy Internet, and blockchain, which provides efficient and effective energy trading in the smart grid. The next chapter will discuss the P2P energy trading scheduling scheme for EVs.

Chapter 3

P2P Energy Trading Scheduling Scheme for Electric Vehicles

In this chapter, we propose an incentive-based P2P energy trading scheduling scheme called as P2P Energy Trading Scheduling *(PETS)* using blockchain technology. PETS is based on real-time energy consumption monitoring for balancing the energy gap between SPs, *i.e.,* smart grids and service consumers, *i.e.,* EVs. Moreover, to design an incentive-based energy trading, there must be sufficient energy at SP for EV users to schedule their battery at the destination. Hence, in PETS, the Stackelberg game theory-based 1-leader multiple-followers scheme is proposed to depict the interactions between EVs and the SP. The selection of the leader among all SPs is done using a second-price reverse auction. As per the announced energy price by the leader, EVs manage energy consumption by minimizing their energy bills. In PETS, on the leader's side, we propose the Genetic algorithm to maximize its profit. In contrast, on the followers' side, *i.e.*, EVs, we use the Stackelberg Equilibrium to minimize their energy bills.

3.1 Contributions

The major research contributions of this chapter are summarized below.

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

The schematic overview of PETS scheme is as shown in Fig. 3.1.

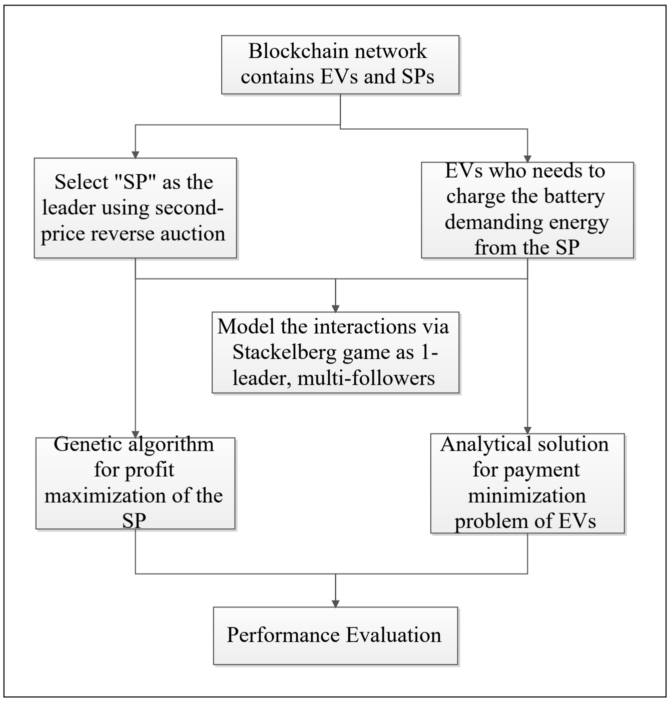


Figure 3.1: Schematic Overview of PETS scheme

3.2 System model

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

3.2.1 Blockchain-based P2P Energy Trading Scheduling Architecture

Fig. 3.2 presents the incentive-based P2P energy trading scheduling model in smart grid systems using blockchain, where N is the number of SPs as $SP = (SP_i : \forall i \in N)$ and n_i is the number of EVs as $EV = (EV_j : \forall j \in n_i)$; whereas, $n_i \subseteq N$ and $i, N = (1, 2, ..., N)$. The energy information processing network has data processors (DPs) to collect and transmit energy data and act as distribution of nodes on the blockchain network. In the system model, DPs are joined as point-to-point communication in a distributed shared information node and maintain the distributed ledger. They are responsible to implement an incentive mechanism and manage the charging-discharging activities of all nodes. Digital signatures are used to provide security and privacy in a real-time P2P energy trading interaction system on a blockchain [227]. It not only assure effective and secure energy trading but also verifies whether the energy trading between EVs and the SP is legal and efficient.

In this model, EV_j wants to buy an energy for charging the battery from SPs. Firstly, SPs, *i.e.,* SP_i submitted a sealed-bid on a blockchain for selling the energy to EVs or to take

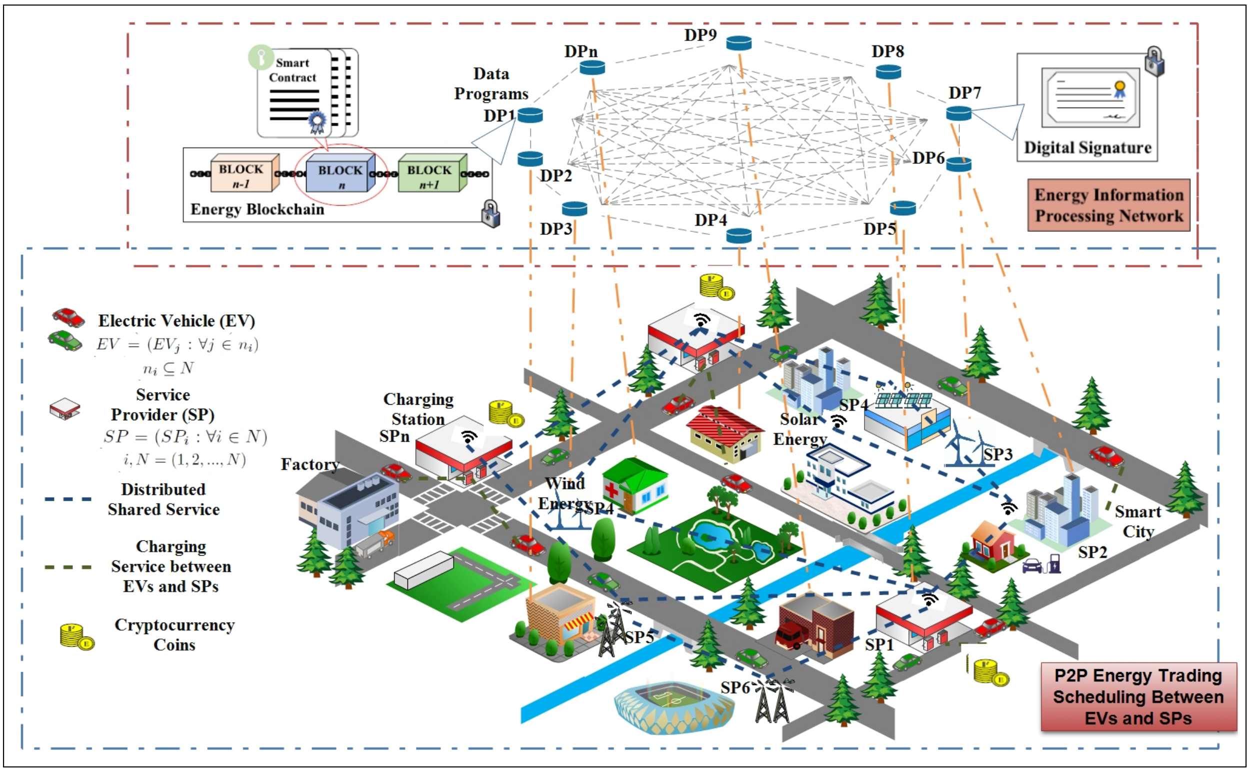


Figure 3.2: Blockchain-based P2P energy trading scheduling scenario

charge of EVs. Then, using a second-price reverse auction based smart contract [143], the SP having lowest bid among all SPs is selected to make it as the leader, *i.e.*, SP_L is as shown in Algorithm 1. Secondly, to design the energy trading interactions between EV_j and the SP_L, we use Stackelberg game theory having 1-leader (SP_L) and multi-followers (EV_j). Moreover, Stackelberg's game theory addresses an incentive-based problem with asymmetric information between EVs and the SP in the PETS scheme.

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

3.2.2 Problem Formulation

3.2.2.1 Optimal real-time pricing consumption for EVs- At follower level

In this section, we define an energy consumption scheduling vector for each EV, *i.e.*, $EV \in EV_j$, $j \subseteq N$. Using this, we can control the hourly use of energy of each EV by defining the energy price. The scheduling vector of energy consumption for each EV is as follows:

$$X_{j,EV} = [x^1_{j,EV}, x^2_{j,EV}, \dots\dots, x^h_{j,EV}] \tag{3.1}$$

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

$$\sum_{h=\gamma_{j,EV}}^{\beta_{j,EV}} x^h_{j,EV} = E_{j,EV} \tag{3.2}$$

$$x^h_{j,EV} = 0, \forall h \in H_{j,EV} \tag{3.3}$$

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

$$\alpha^{min}_{j,EV} \leq x^h_{j,EV} \leq \alpha^{max}_{j,EV}, \forall h \in H_{j,EV} \tag{3.4}$$

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

$$\begin{aligned} min\, EV = min \sum_{h=1}^{H} p^h \times \left(\sum_{EV \in EV_j} x^h_{j,EV} \right) \\ s.t. \\ C_1 : \sum_{h=\gamma_{j,EV}}^{\beta_{j,EV}} x^h_{j,EV} = E_{j,EV}, \\ C_2 : x^h_{n_i,EV} = 0, \forall h \in H_{j,EV}, \\ C_3 : \alpha^{min}_{j,EV} \leq x^h_{j,EV} \leq \alpha^{max}_{j,EV}, \forall h \in H_{j,EV} \end{aligned} \tag{3.5}$$

Algorithm 1 Selection of the Leader

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

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

3.2.2.2 Profit maximization model for SPs- At leader level

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

$$Cost_h(P_h) = m_h P_h^2 + q_h P_h + r_h \tag{3.6}$$

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

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

$$\sum_{n \in N} \sum_{a \in EV_j} x_{j,a}^h \leq Energy_h^{max}, \forall h \in H \tag{3.7}$$

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

$$\begin{aligned} & max \left\{ \sum_{h \in H} p^h \times \sum_{n \in N} \sum_{a \in EV_j} x_{j,a}^h - \right. \\ & \qquad \left. \sum_{h \in H} Cost_h \left(\sum_{n \in N} \sum_{a \in EV_j} x_{j,a}^h \right) \right\} \\ & s.t. \\ & C_1 : p^{min} \leq p^h \leq p^{max} \\ & C_2 : \sum_{n \in N} \sum_{a \in EV_j} x_{j,a}^h \leq Energy_h^{max}, \forall h \in H, i, j \in N \end{aligned} \tag{3.8}$$

3.2.2.3 Stackelberg Game Model

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

1. For each strategy of SP_L is $s_L \in S_{L_N}$, EVs try to minimize the payment function to get the

best response $R_{F_j}(s_L)$ as follows:

$$\min_{s_{F_j} \in S_{F_j}} J_{F_j}(s_L, s_{F_j}) = min \sum_{h=1}^{H} p^h \times \left(\sum_{a \in EV_j} x_{j,a}^h \right) \tag{3.9}$$

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

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

$$\begin{aligned} &\max_{s_L \in S_L} J_L(s_L, R_{F_1}(s_L), ..., R_{F_j}(s_L)) \\ &= max \left\{ \sum_{h \in H} p^h \times \sum_{n \in N} \sum_{a \in EV_j} x_{j,a}^h - \right. \\ &\left. \sum_{h \in H} Cost_h \left(\sum_{n \in N} \sum_{a \in EV_j} x_{j,a}^h \right) \right\} \end{aligned} \tag{3.10}$$

3. Let s_L^* be the optimal strategy solution for P2P energy trading problem and $s_{F_j}^* = R_{F_j}(s_L^*)$. $\left(s_L^*, s_{F_1}^*, s_{F_2}^*, ..., s_{F_j}^*\right)$
   It is called as Stackelberg game strategy (Equilibrium) and the structure of Stackelberg game model is as shown in Fig. 3.3.

3.3 P2P Energy Trading Scheduling Scheme

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

3.3.1 Optimal real-time energy consumption scheduling for EVs

For all EVs, the payment minimization problem is defined in Eq. 3.5, which is a linear programming problem. We design a systematic solution for this payment minimization problem as follows.

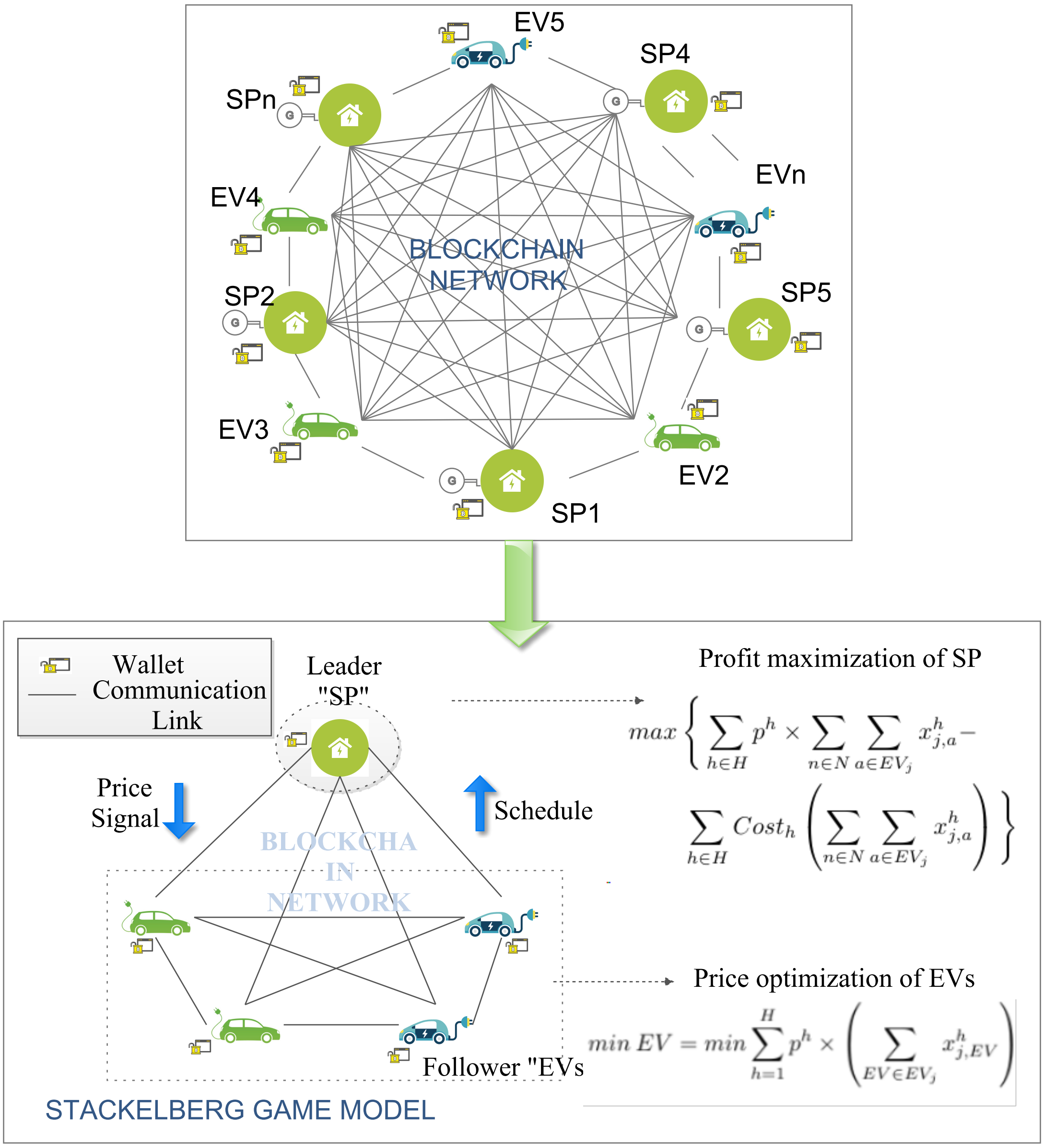


Figure 3.3: The Stackelberg game model

The payment minimization of problem Eq. 3.5 is redefined as follows:

$$min \sum_{EV \in EV_j} \left(\sum_{h=1}^{H} p^h \times x_{j,EV}^h \right) \tag{3.11}$$

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

$$\begin{aligned} & min \sum_{EV \in EV_j} f_{EV}(x_{EV}) \\ & s.t. \\ C_1 : & a \leq g_{EV}(x_{EV}) \leq b. \forall EV \in EV_j \\ C_2 : & h_{EV}(x_{EV}) = c, \forall EV \in EV_j \end{aligned} \tag{3.12}$$

and the optimal solution for this optimization problem is same as Eq. 3.12 and is computed as:

$$\begin{aligned} & min f_{EV}(x_{EV}) \\ & s.t. \\ C_1 : & a \leq g_{EV}(x_{EV}) \leq b. \forall EV \in EV_j \\ C_2 : & h_{EV}(x_{EV}) = c, \forall EV \in EV_j \end{aligned} \tag{3.13}$$

We decompose the payment minimization problem Eq. 3.11 of $|EV_j|$ into small problems, such that $|EV_j|$ is the number of EVs used in EV_j and is computed as follows:

$$\begin{aligned} & min \sum_{h=1}^{H} p^h \times x_{j,EV}^h \\ & s.t. \\ & C_1 : \sum_{h=\gamma_{j,EV}}^{\beta_{j,EV}} x_{j,EV}^h = E_{n_i,EV}, \forall EV \in EV_j \\ & C_2 : x_{j,EV}^h = 0, \forall h \in H_{j,EV}, \forall EV \in EV_j \\ & C_3 : \alpha_{j,EV}^{min} \leq x_{j,EV}^h \leq \alpha_{j,EV}^{max}, \forall h \in H_{j,EV}, \forall EV \in EV_j \end{aligned} \tag{3.14}$$

After that $H = (\gamma_{j,EV}, ..., \beta_{j,EV})$, $x^h_{n_i,EV} = 0$, $\forall h \in H_{j,EV}$, and $\forall EV \in EV_j$, we represent the Eq. 3.14 as follows:

$$\begin{aligned} & min \sum_{h=\gamma_{j,EV}}^{\beta_{j,EV}} p^h \times x^h_{j,EV} \\ & s.t. \\ & C_1 : \sum_{h=\gamma_{j,EV}}^{\beta_{j,EV}} x^h_{j,EV} = E_{j,EV}, \forall EV \in EV_j \\ & C_2 : \alpha^{min}_{j,EV} \leq x^h_{j,EV} \leq \alpha^{max}_{j,EV}, \forall h \in H_{j,EV}, \forall EV \in EV_j \end{aligned} \tag{3.15}$$

To solve the Eq. 3.15, the following steps are used.

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

  $= \left[\alpha^{max}_{j,EV}, ..., \alpha^{max}_{j,EV}, x^*_{j,EV}, \alpha^{min}_{j,EV}, ..., \alpha^{min}_{j,EV}\right]$,

  whereas, $\alpha^{min}_{j,EV} \leq x^*_{j,EV} \leq \alpha^{max}_{j,EV}$,

  If $\alpha^{max}_{j,EV}, ..., \alpha^{max}_{j,EV} = m$ then,

  $\alpha^{min}_{j,EV}, ..., \alpha^{min}_{j,EV} = M - m - 1$

  Substitute, $x'_{j,EV}(\gamma_{j,EV} : \beta_{j,EV})$ into C_1 of Eq. 3.15 to compute the following:

  $$m.\alpha^{max}_{j,EV} + x*_{j,EV} + M - m - 1.\alpha^{min}_{j,EV} = E_{j,EV} \tag{3.16}$$

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

  $$m = \frac{E_{j,EV} - M.\alpha^{min}_{j,EV}}{\alpha^{max}_{j,EV} - \alpha^{min}_{j,EV}} \tag{3.17}$$

  whereas, [.] means capturing the nearest integer value.

Adding the value m to the Eq. 3.16, we get $x*_{j,EV}$.

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

Algorithm 2 presents the analytical solution for payment minimization problem.

Algorithm 2 Payment Minimization Problem

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

```
procedure FUNCTION($Price, \alpha^{min}_{j,EV}, \alpha^{max}_{j,EV}, E_{j,EV}, H_{j,EV}$)
    As per $H_{j,EV}$, we get $Price(\gamma_{j,EV} : \beta_{j,EV})$,
    Sort $Price(\gamma_{j,EV} : \beta_{j,EV})$ to get $Price'(\gamma_{j,EV} : \beta_{j,EV})$,
    Using Eqs. 3.16 and 4.23, we get $x*_{j,EV}$ and $x'_{j,EV}(\gamma_{j,EV} : \beta_{j,EV})$,
    Sort inversely $x'_{j,EV}(\gamma_{j,EV} : \beta_{j,EV})$ to get $x_{j,EV}(\gamma_{j,EV} : \beta_{j,EV})$,
    Using $h \in H_{j,EV}$, we have $x^h_{j,EV} = 0$ and then, we find $\left(x^1_{j,EV}, x^2_{j,EV}, ..., x^h_{j,EV}\right)$,
    return $x_{j,EV}$
end procedure
```

3.3.2 Profit maximization for the leader SP

For SP_L profit maximization, we use search-based Genetic algorithm that includes selection, crossover, and mutation operations on a present population and create an optimal or near-optimal solution. The profit maximization problem for SP_L is presented in Eq. 3.8, which is constrained optimization so we use penalty function as follows:

$$
\begin{aligned}
& min\, f(\bar{x})\, \bar{x} \in Feasible \subset R^n \\
& \quad s.t. \\
& C_1 : a_i(\bar{x}) = 0,\, i = 1, 2, ..., m \\
& C_2 : b_j(\bar{x}) \le 0\; j = m+1, ..., p
\end{aligned}
\tag{3.18}
$$

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

$$Evaluation(\bar{x}) = \begin{cases} f(\bar{x}) & if\, \bar{x} \in Feasible \\ K - \sum_{i=1}^{s} \frac{K}{m} & \text{otherwise} \end{cases} \tag{3.19}$$

whereas, m is the total constraints, s is non-violated constraints, and K is a constant with value 1×10^9 [228].

As defined in the Eq. 3.8, the profit maximization problem is solved by the Genetic algorithm. The five phases of the Genetic algorithm, *i.e.,* (i) population (ii) fitness evaluation, (iii)selection, (iv) crossover, and (v) bit flip mutation, which finds an optimal solution for profit maximization problem for SP_L. A brief description of each phase of the Genetic algorithm is described as follows.

1. **Population:** In this phase, we use a binary-coded representation of the population in the PETS scheme. As defined in Eq. 3.8, we set the parameters, *i.e.,* $8 \leq p^h \leq 14$ cents and length of binary digits after the decimal point is up to two places related to the values and precision of the variables, *i.e.,* 10^2. The length of the binary bits is represented as $length_b$ and is set as 10. Hence, we compute the $p^{max} - p^{min}$, which is defined as follows:

   $$2^{length_b - 1} \leq p^{max} - p^{min} \times 1/10^{-2} \leq 2^{length_b} \tag{3.20}$$

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

   $$\begin{aligned} 2^9 \leq (14-8) \times 10^2 \leq 2^{10} \\ 2^9 \leq 600 \leq 2^{10} \end{aligned} \tag{3.21}$$

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

2. **Fitness Evaluation:** In this phase, we evaluate the objective function defined in Eq. 3.6 for each chromosome produced in the population phase, which is defined as follows.

   $$Cost_h(P_h) = m_h P_h^2 + q_h P_h + r_h \tag{3.22}$$

3. **Selection:** In this phase, we use tournament selection process for the binary representation based population defined in the PETS scheme. First, we choose two random individuals from the population and then, select the better one into the mating pool. The steps involved in the selection process is defined in the Algorithm 3. After the selection of the

Algorithm 3 Selection Process

```
Input: Population ($Pop_1, Pop_2, ..., Pop_N$).
Size of tournament $t$ = 2.
Output: $Pop'_1, Pop'_2, ..., Pop'_N$.
procedure FUNCTION($N$)
    for $(i = 1; i \leq N; i++)$ do
        $Pop'_i \leftarrow$ best individual chosen from ($Pop_1, Pop_2, ..., Pop_N$) by picking 't' individuals randomly
    end for
    Return ($Pop'_1, Pop'_2, ..., Pop'_N$)
end procedure
```

best individuals, we use elitism to make a copy of these individuals in the next generation. The steps involved for elitism in the selection process is described in the Algorithm 4.

Algorithm 4 Elitism Process

```
procedure FUNCTION($P$)
    Generate a random $P$ population.
    Evaluate the $P$ population and choose the $C_{best}$ chromosome.
    Apply the operations, i.e., selection, crossover, and mutation to get new $P'$ population.
    Then, choose the $C'_{best}$ and $C'_{worst}$ chromosome represents the best and worst, respectively.
    if $C'_{best} \leq C_{best}$ then
        $C'_{worst} = C_{best}$
    else
        No replacement
    end if
    Repeat from the step 2.
end procedure
```

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

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

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

Algorithm 5 Uniform Crossover

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

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

the profit using fitness evaluation. Lastly, after the finite number of iterations, an optimal profit price for SP_L and minimized payment bill having best response for EVs is obtained.

3.3.3 Complexity Analysis

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

3.3.3.1 Time Complexity

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

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

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

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

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

Algorithm 6 Profit Maximization Problem

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

```
1: procedure FUNCTION($N$)
2:     for $(i = 1; i \leq N; i++)$ do
3:         The $SP_L$ plays a strategy $s_L$ and set the prices of 24-hour time by solving the $i_{th}$ chromosome.
4:         The EVs $EV_j$ react on $SP_L$'s strategy, i.e., $s_{L,i}$ by a best response $s_{F_{j,i}} = R_{F_j}(s_{L,i})$ and solve a payment minimization problem to find an optimal energy consumption scheduling as in Eq. 3.5.
5:         By fitness evaluation based on $s_{L,i}$ and $s_{F_{j,i}}$, we find to solve profit maximization problem as in Eq. 3.8.
6:     end for
7:     By using Selection, Crossover, and Mutation operations, created a population of new chromosomes.
8:     Goto steps 2 to 7 until the problem solves.
9: end procedure
```

computation of Algorithm 6 is *O(N) + O(1) = (O(N)).*

3.3.3.2 Space Complexity

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

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

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

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

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

3.4 Performance Evaluation

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

3.4.1 Numerical Settings

In this section, we describe the simulation settings and parameters to evaluate the proposed PETS scheme. For simulation, we considered the EVs charging data having 113 customers for the period of January 2013 to June 2014 [229]. From this data set, we received half-hourly KWh measurements from the EV chargers. The scheduling period for the EVs are from 8 AM to 8 AM the next day.

For the price of the energy given to the EVs by the SP, we proposed a scheduling scheme having a cost function of quadratic nature ($Cost_h(P_h) = m_h P_h^2 + q_h P_h + r_h$) is redefined as in Eq. 3.6. Let us assume the values, *i.e.,* $q_h = 0$ and $r_h = 0$ to evaluate the cost function for maximizing the profit for SPs by minimizing the payment bills by EVs. Also, we use $m_h = 5.5 \times 10^{-4}$ cents during the day (8 AM to 12 AM) and $m_h = 4.0 \times 10^{-4}$ cents at night time (12 AM to 8 AM the next day).

3.4.2 Results and Discussions

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

3.4.2.1 Impact on EVs energy load

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

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

$$P_h = \sum_{j=N} EV_j^h \tag{3.23}$$

Then, the peak and average load of EVs are computed as follows.

$$P_{Peak} = \max_{h \in H} P_h \tag{3.24}$$

$$P_{Avg} = \frac{1}{H} \Big(\sum_{h \in H} P_h \Big) \tag{3.25}$$

Hence, PAR is defined as follows:

$$PAR = \frac{P_{Peak}}{P_{Avg}} = \frac{H \times \max_{h \in H} P_h}{\sum_{h \in H} P_h} \tag{3.26}$$

From Fig. 3.4, we have observed that in the proposed PETS scheme, the average PAR in energy load of EVs reduces by 12.5% as compared to the existing scheme [223]. [h!]

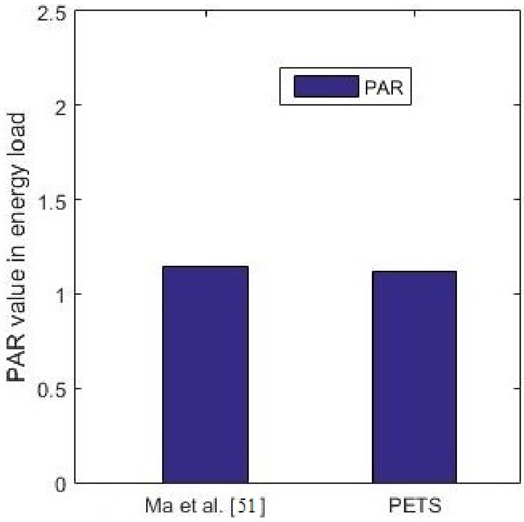


Figure 3.4: PAR of the EVs load

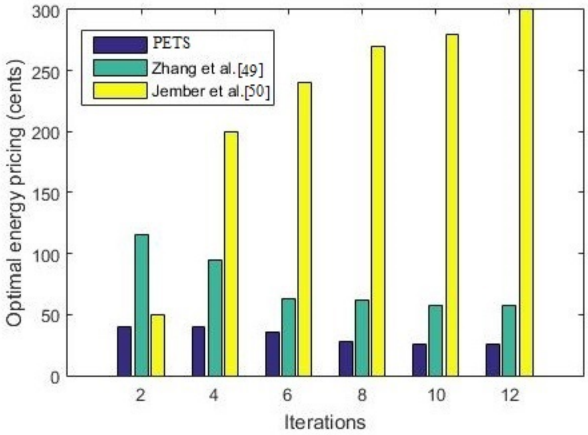


Figure 3.5: Convergence of best response in PETS

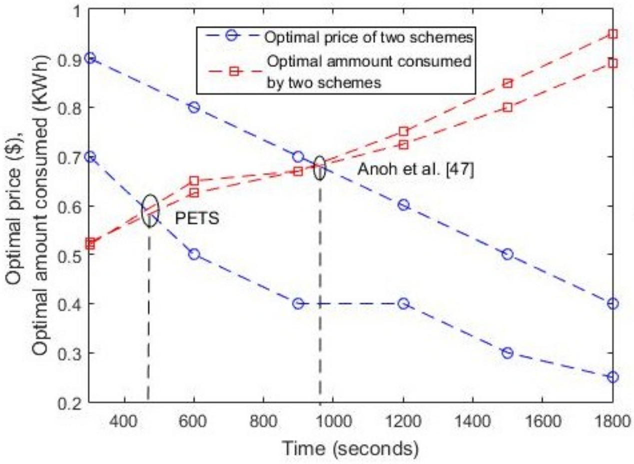


Figure 3.6: Optimal pricing at different periods of PETS with the existing scheme

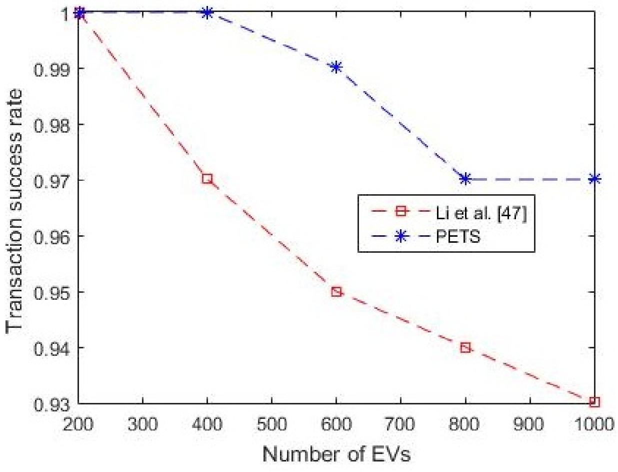


Figure 3.7: Transaction matching rate of PETS with the existing scheme

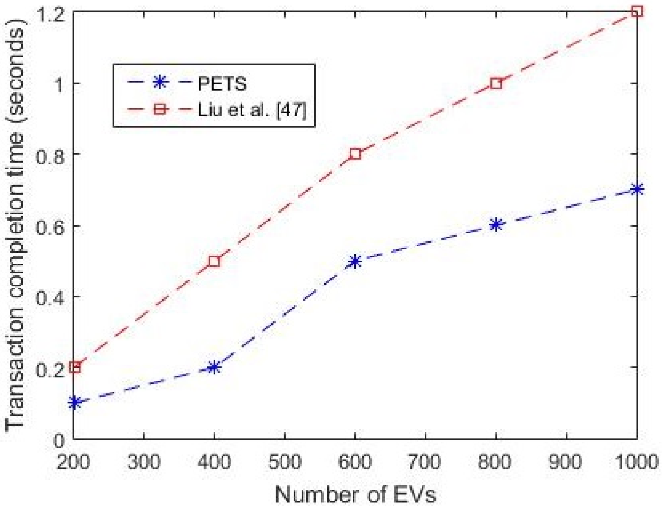


Figure 3.8: Transaction efficiency curve of PETS with the existing scheme

3.4.2.2 Impact on energy pricing

This section describes the impact of the proposed PETS scheme on the optimal energy pricing of SPs. Fig. 3.5 shows the concurrence of best response and the convergence of optimal energy pricing of SPs in the proposed PETS scheme. It clearly shows that the proposed scheme converges after *ten* iterations to one equilibrium point compared to the existing schemes, *i.e.,* converges within 15 iterations [221] and after 15 iterations [222]. Fig. 3.6 shows the prices decrease as the trading period increases. EVs consume more energy at lower prices while SP sells more at a higher price. This figure shows the equilibrium point of price where both EVs and the SP found an acceptable price. In comparison to the existing scheme [165], the proposed PETS scheme have an unique equilibrium point with respect to time as shown in Fig. 3.6. Hence, the evaluation based on the proposed PETS scheme declares the capability and better convergence in optimal pricing for SPs compared to the existing schemes.

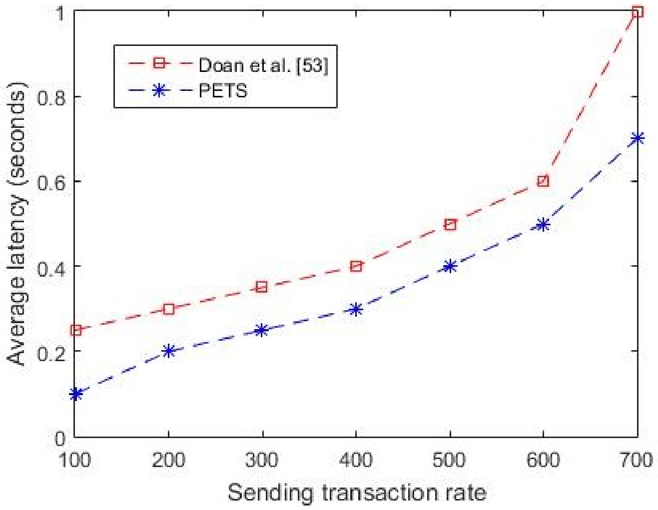


Figure 3.9: Average latency of PETS with the existing scheme

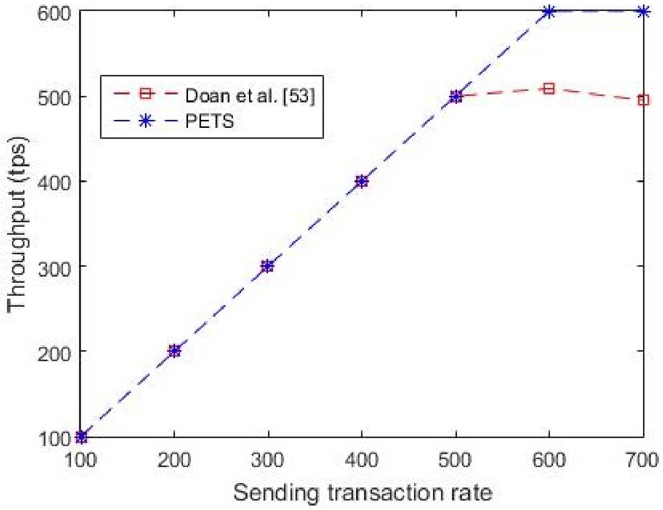


Figure 3.10: Throughput of PETS with the existing scheme

3.4.2.3 Impact on transactions

This section describes the impact of the proposed PETS scheme on energy transactions. The comparison of two schemes for the transaction success rate is as shown in Fig. 3.7. It shows that the transaction rate is high when less number of EVs participate in P2P energy trading scheduling. Compared to the existing scheme [159], the proposed PETS scheme have a superior transaction success rate. Also, in Fig. 3.8, when less number of EVs have participated in P2P energy trading, the time taken to complete the transaction is less in both the schemes. However, with an increase in EVs, the transaction completion time is also increasing. Compared to the existing scheme [159], the proposed PETS scheme takes less time to complete the transactions, which improves the transaction efficiency. From the results obtained, it can be inferred that the proposed PETS scheme supports fast and secure P2P energy trading.

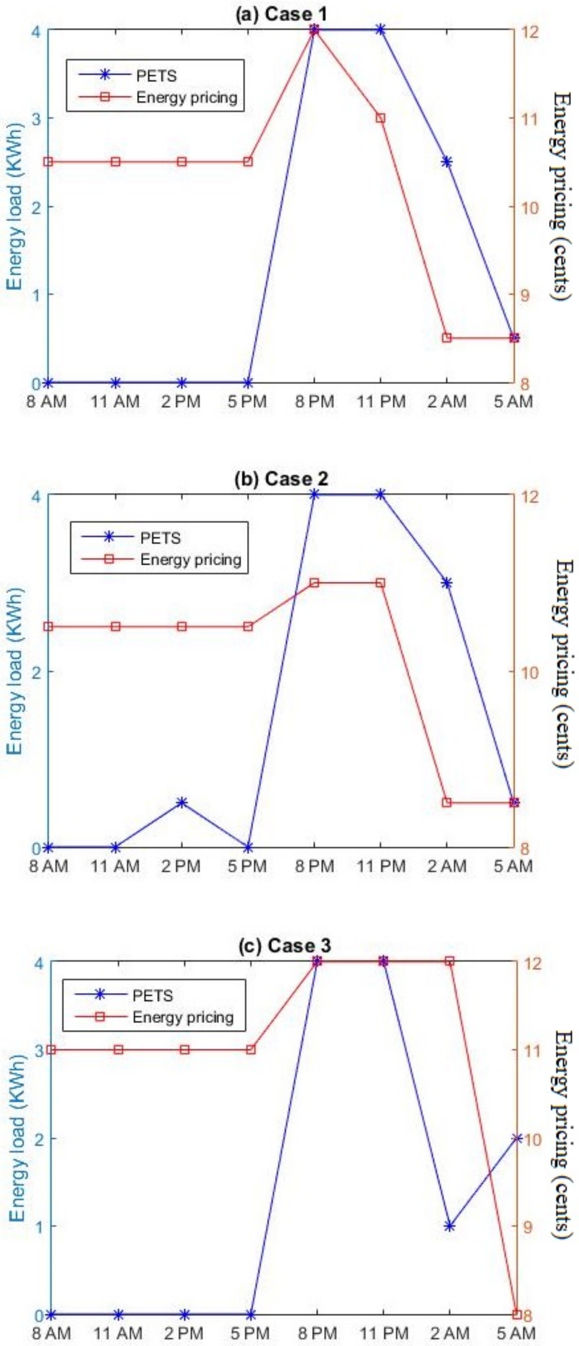


Figure 3.11: Energy consumption for different EVs using PETS

3.4.2.4 Impact on scalability

This section describes the impact of the proposed PETS scheme on the scalability of the system model. We simulated PETS at different transaction rates from 100 to 700 tps with a message count of 50 and batch processing time of 0.5 seconds. Compared to the existing scheme [180], the proposed PETS scheme performs better in scalability metrics, i.e., average latency and throughput, are shown in Fig. 3.9 and Fig. 3.10, respectively.

Table 3.1: Time-of-use tariff time bands

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

3.4.2.5 Impact of scheduling time

In this section, we use ToU price for EVs where we partition the time, *i.e.,* 24 hours into three different bands such as peak, off-peak and day for every weekday [229]. The structure of ToU tariff bands is shown in Table 3.1.

We have tested the genetic algorithm on three test cases, *i.e.,* Case 1: 24, Case 2: 90, and Case 3: 91 EVs are reported for evaluation. Fig. 3.11 clearly shows the daily payment of EVs. It shows that with the deployment of the proposed PETS scheme, the energy consumption of EVs is deviated from high prices to low in comparison to non-scheduling EVs.

3.5 Summary

In this chapter, we propose an incentive-based PETS scheme based on energy consumption real-time pricing using blockchain technology in smart grid systems. We have considered EVs to minimize their energy payment bills and SPs to maximize their profit. The interactions between EVs and the SP have been modelled using the Stackelberg game theory-based 1-leader, multi-followers, where SP_L is the leader and EVs are followers. It provides a powerful mechanism to address the problem of EVs with asymmetric information. Our scheme is based upon the following. Firstly, we selected the leader among all SPs using a second-price reverse auction. Then, EVs are scheduled at SP for charging their battery. For optimization, we used an analytical solution to minimize the energy consumption bills of EVs and used the Genetic algorithm to maximize SP's profit. Simulation results show that the proposed PETS scheme outperforms the existing scheme concerning the various performance evaluation metrics in terms of PAR value, latency, throughput, and scalability. In the next chapter, we will discuss the demand response management scheme between EVs and the SPs.

Chapter 4

Consortium Blockchain-based Energy Trading for Demand Response Management

In this chapter, we propose a P2P energy trading scheme between EVs and SPs to manage the demand response in the V2G environment. Unlike centralized architectures that include complex energy trading mechanisms, the proposed one attains an energy balance between demand and supply. However, the security and privacy protection of online transactions of EV users pose several challenges concerning confidentiality, integrity, and authorization. Therefore, we design a consortium blockchain that ensures secure energy transactions between EVs and the SPs without any involvement of a trusted third party. Moreover, the energy pricing and the amount of traded energy problems for demand response are solved by a double auction mechanism to maximize social welfare. Here, the blockchain network works as an auctioneer to conduct the auction according to their bid prices, which does not require private information about EVs. Numerical results based on a real-time implementation indicate that a double auction mechanism maximizes social welfare.

4.1 Contributions

Based on the above discussions, the following contributions are presented in this research work.

- A blockchain-based secure energy trading scheme for demand response management between the EVs and the SPs is presented.
- To optimize energy pricing and the amount of traded energy, a double auction mechanism is proposed between EVs and SPs to maximizes social welfare with privacy preservation.

- To validate the proposed scheme, we designed a framework for a private Ethereum network. The framework is based on lightweight virtualization and supports dynamic configuration of the network.
- We evaluated the proposed scheme using different performance evaluation parameters to test its efficacy in comparison to the existing state-of-the-art proposals.

4.2 System Model

A blockchain-based secure energy trading model between EVs and SPs in a V2G environment is as shown in Fig. 4.1. The interaction between the EVs and the SPs realizes V2G services through energy trading in demand response management. This system model consists of three main entities, *i.e.,* EVs, SPs with generator, and the blockchain network. Each node on the blockchain network has its own ledger with a wallet address that stores the energy transaction history and accepts the digital cryptocurrency at the time of energy trading for demand response management. The information stored on the blockchain network is transparent and immutable. So, no hacker or malicious activity can change the blockchain data because it has been secured by cryptographic hash primitives. The functionality and speciality of each entity in which EVs represent the demand side and SPs represent the supply side are described as follows.

4.2.1 Electric Vehicles

EVs play a vital role in a V2G environment. They have the capability of bi-directional energy trading. They can act as energy producers and provide electricity by discharging their battery during peak time. On the other side, they can also act as energy consumers by charging their battery with electricity during the peak-off time. They can adjust their charging and discharging nature and actively participate in a V2G energy trading to maximize their payoff. The interactions of the EVs with the grid realize V2G services through a two-way flow of energy, *i.e.,* energy flow from the EVs to the grid and the grid can send this energy to EVs at peak time. In this chapter, as a consortium blockchain-based system, EVs can communicate to SPs for charging the batteries. Those EVs who need electricity services can determine their service demand to purchase the energy. They take energy services from those SPs, which have fewer energy prices on the blockchain network.

4.2.2 Service Providers

SPs with incorporated control of integrated communication resources and computing resources provide energy services to the EVs. To have an energy trading connection between EVs and SPs, SPs announce a reasonable price to the EVs for selling the services. EVs can

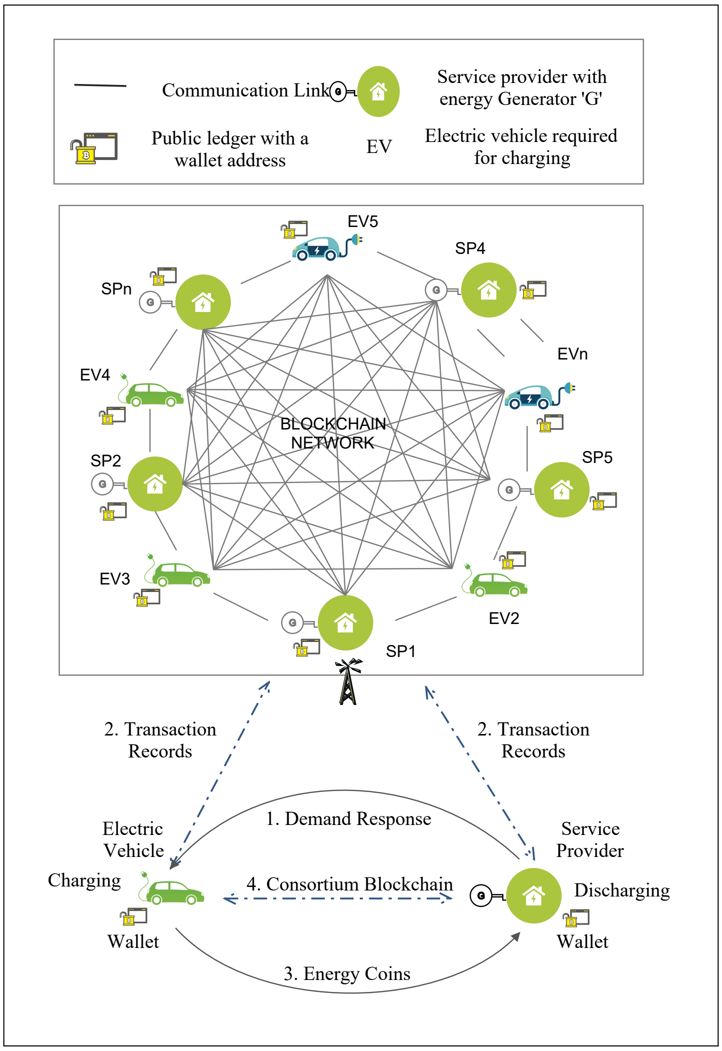


Figure 4.1: System model

drive their service demand for purchasing services based on the announced prices. Each SP has its own generator that generates the energy for energy trading during the peak timings. So, there is no need to charge the SPs as it has its own generator to produce energy from renewable energy resources.

4.2.3 Blockchain Network

The operation of the blockchain-based secure energy trading scheme for demand response management is described as follows. In the beginning, the nodes of the blockchain network register a request to the certifying authority for obtaining a public key (PU) and a private key (PK) using Public-key infrastructure (PKI) to ensure integrity and wallet security [230]. These keys are generated and distributed by a legitimate authority. This authority provides a unique token to the nodes for identity through the registration information as shown in the Fig. 4.2. Nodes find the wallet address by adding them into the blockchain network for demand response management, which is described in the next section.

The blockchain network designs a scheme, which specifies the relationship between the EVs and the SPs, *i.e.,* amount of energy needed by EVs from the SPs and the reward, *i.e.,* payment to the SPs in terms of energy coins [177]. Each node on the blockchain network has an account to store all transaction records, and the corresponding wallet for managing energy coins in the account. During P2P energy trading for demand response management, first EVs send request for energy demand on the blockchain network then, the corresponding SPs accepted an energy request and submit bids for selling the energy according to their supply. Nodes on the blockchain network act as energy brokers for EVs and the SPs to execute energy bidding and transaction through a double auction mechanism. The energy coins are transferred to the wallet address of SPs from the wallet address of the EVs. The authentication of the payment can be verified by checking the last block of the blockchain. The new transaction record is verified and digitally signed by the nodes then, only broadcasted on a consortium blockchain (Fig. 4.1).

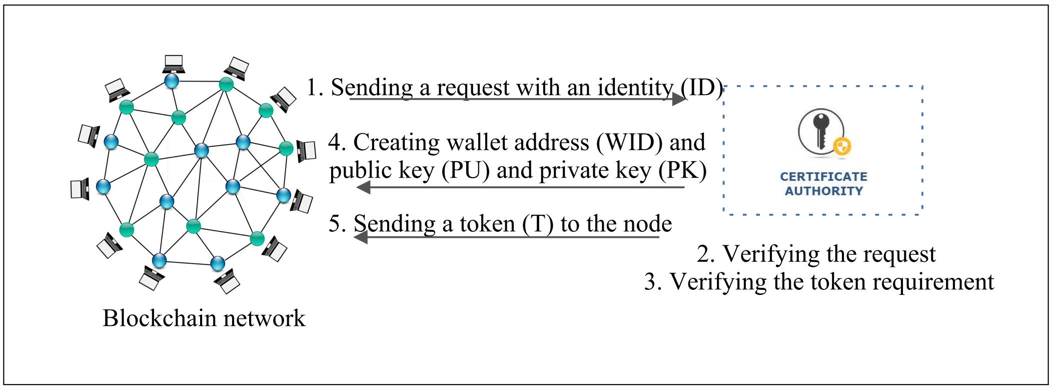


Figure 4.2: Token registration of the nodes on blockchain network

All the transactions are done between the EVs and the SPs are collected and recorded within a certain amount of time. Then, these transactions are encrypted, digitally signed, and structured into blocks. Also, these blocks are broadcasted on the blockchain network for verification and validation, which is done by Proof of Authority (PoA) consensus mechanism. Fake and invalid transactions are discarded. PoA is one of the most mature versions of blockchain technology. It is faster than other algorithms, more scalable, and does not depend on mining. Unlike PoW and PoS, it does not require miners to be involved at all. The rights to generate new blocks are awarded to nodes that have proven their authority to do so, which is known as *Validators*. They need to confirm their real identities to approve their accounts. A node must be willing to invest money and put his reputation at stake. A tough process reduces the risks of selecting questionable validators and incentivize long-term commitment to the blockchain. The method for selecting validators must be equal to all nodes. The identity of validators must be verified to maintain the integrity of the blockchain. As a result, there is no need to spend vast amounts of resources to maintain the network's performance. The authority of the node is the guarantor of the transaction's validity. Therefore, such a network is protected against manipulation by the owners of richer nodes. Also, PoA validators must pass a series of checks to confirm the reliability of the system model.

4.3 Problem Definition

In this section, we present the problem definition of energy pricing and the amount of energy traded between the EVs and the SPs to maximize the overall social welfare (i.e., the sum of nonlinear utilities). In any region, for establishing a real-time energy trading market for demand response management, a blockchain enriched smart contract can communicate with EVs and the SPs. Nodes of the blockchain network '$Node_n$' can facilitate energy trading between them and acting as an energy broker, which manages local EVs to execute energy trading operations for demand response management. A number of nodes (EVS and SPs) is denoted by n, where n $\in Node_n \triangleq$ (1,2,3..n). Let us denote a set of charging EVs in the blockchain network as $EV \triangleq (EV_i^n | i \in E, n \in Node_n)$, (E =0,1,2,3..I). The discharging SPs in the blockchain are denoted as $SP \triangleq (SP_j^n | j \in Z, n \in Node_n)$, (Z =0,1,2,3..J). $e_i^{n,min}$ and $e_i^{n,max}$ are the minimum and maximum energy needed for $EV_i^n \in Real$ on the blockchain network, respectively. So, the $Node_n$ must provide $e_i^{n,min}$ energy to EV_i^n for normal driving.

Here, e_{ij}^n is the energy demand of EV_i^n for discharging supply by SP_j^n in $Node_n$. The energy demand vector of EV_i^n is $E_i^n \triangleq (e_{ij}^n | j \in Z)$. In the blockchain network $Node_n$, the total energy demand of all the charging EVs is $E^n \triangleq (E_i^n | i \in E)$. The state of energy before charging the EVs' battery is SoC_i^n and the battery capacity of an EV_i^n is EV_i^{cap}. The satisfaction function U_i of EV_i^n is :

$$U_i(E_i^n) = w_i[ln(\eta \sum_{j=1}^{J} (e_{ij}^n - e_i^{n,min}) + 1)] \qquad w_i = \sigma / SoC_i^n \tag{4.1}$$

where, w_i is the charging willingness of EV_i^n, η is an average charging efficiency from discharging, and σ is a constant.

For SPs, s_j^n is the amount of energy supply from SP_j^n to the EV_i^n in the $Node_n$. The energy supply for demand response management vector of SP_j^n is $S_j^n \triangleq (s_{ji}^n | i \in Real)$. In the blockchain network $Node_n$, the total energy supply of SP_j^n is $S^n \triangleq (S_j^n | j \in Z)$. The maximum energy supply is $S_j^{n,max}$. So, the cost function L_j of SP_j^n is:

$$L_j(S_j^n) = c_1 \sum_{i=1}^{I} (s_j^n)^2 + c_2 \sum_{i=1}^{I} (s_{ji}^n), \tag{4.2}$$

where c_1 and c_2 are cost factors and $c_1 \geq 0$.

Since the EVs want to maximize their utilities while the SPs try to minimize their cost, whereas $Node_n$ of the blockchain network not only tries to meet the demand of EVs and SPs, but also maximize energy allocation efficiency for demand response management. The blockchain network addresses the social welfare maximization problem (SWM) to allocate energy between the EVs and the SPs for demand response management. Here, the objective function of SWM problem is described as follows:

$$SWM: \max_{E_n,S_n} \sum_{i=1}^{I} U_i(E_i^n) - \sum_{j=1}^{J} L_j(S_j^n) \tag{4.3}$$

$$\begin{aligned} Subject\,to: e_i^{n,min} \leq \eta \sum_{j=1}^{J} e_{ij}^n \leq e_i^{n,max}, \forall_i \in E, \\ \sum_{i=1}^{I} s_{ji}^n \leq S_j^{n,max} \forall_j \in Z, \\ \rho s_{ji}^n = e_{ij}^n, \forall_i \in E, \forall_j \in Z, \\ e_{ij}^n \geq 0, \forall_i \in E, \forall_j \in Z,. \end{aligned} \tag{4.4}$$

Here, ρ is an average energy transmission efficiency for demand response management between the EVs and the SPs. The objective function in Eq. (4.3) is concave with compact and convex constraints, so there exists a unique optimal solution using the method Lagrangian multipliers (non-linear programming solution technique).

$$\begin{aligned} L_1(E^n, S^n, \lambda, \beta, \alpha, \gamma, \theta) = \sum_{i=1}^{I} U_i(E_i^n) - \sum_{j=1}^{J} L_j(S_j^n) \\ + \sum_{i=1}^{I} \lambda_i (e_i^{n,min} - \eta \sum_{j=1}^{J} e_{ij}^n) + \sum_{i=1}^{I} \beta_i (\eta \sum_{j=1}^{J} e_{ij}^n - e_i^{n,max}) + \\ \sum_{j=1}^{J} \alpha_j (\sum_{i=1}^{I} s_{ji}^n - S_j^{n,max}) + \sum_{i=1}^{I} \sum_{j=1}^{J} \gamma_{ij} (\rho s_{ji}^n - e_{ij}^n) \\ - \sum_{i=1}^{I} \sum_{j=1}^{J} \theta_{ij} e_{ij}^n \end{aligned} \tag{4.5}$$

Here, $\lambda_i, \beta_i, \alpha_j, \gamma_{ij}, \theta_{ij}$ are Lagrange multipliers for the constraints in Eq. 4.4. Hence, the optimal solution of *'SWM'* meets following conditions:

$$\begin{aligned} \nabla_{e_{ij}^n} L_1(E^n, S^n, \lambda, \beta, \alpha, \gamma, \theta) = \frac{\eta w_i}{(\eta \sum_{j=1}^{J} e_{ij}^n - e_i^{n,min}) + 1} \\ - \eta \lambda_i + \eta \beta_i - \gamma_{ij} - \theta_{ij} = 0 \end{aligned} \tag{4.6}$$

$$\begin{aligned} \nabla_{s_{ij}^n} L_1(E^n, S^n, \lambda, \beta, \alpha, \gamma, \theta) = -2c_1 s_{ji}^n - c_2 \\ + \alpha_j + \rho \gamma_{ij} = 0 \end{aligned} \tag{4.7}$$

For the SWM problem, it is necessary that the blockchain network has true and complete information of all EVs' utility and cost functions, and thus to solve the problem using Eqs. 4.6 an

4.7.

4.4 Auction Mechanism

In this section, we have used an auction mechanism to maximize the social welfare problem between the EVs and the SPs for demand response management. Initially, a sealed-bid first price reverse auction has been used to find the lowest bid from all the submitted bids by the SPs to charge the battery of the EVs. Then, a double auction has been used to find the final trading prices and the amount of traded energy for demand response management, which is useful and ensures information asymmetric of EVs. More specifically, each charging EV $'EV_i'$ mentions the required energy for charging with auction bid price $b_{ij} \geq 0$ on the blockchain network. In order to response EV_i, each SP_j submits a different bid price $p_{ji} \geq 0$ on the blockchain network. Here, blockchain having smart contracts acts as an auctioneer to perform a reverse auction according to buying prices from the EVs and selling prices from the SPs. After receiving these prices, the auctioneer solves the selection of *'SP'* problem, and thus allocates SP_j (having lowest-bid from all the submitted bids) to the EV_i for demand response management to achieve effective price market as described in the Algorithm 7.

4.4.1 Different Roles in Auction Mechanism

The nodes used in the blockchain network are working under the auction mechanism and their description is described as follows.

- **Electric Vehicles:** The bid price vector of EV_i^n to buy a energy for charging the battery from SPs on the blockchain network is $Bid_i^n = (b_{ij}^n | j \in Z)$. All bid prices of the EVs on the blockchain network are denoted as $B^n = (Bid_i^n | i \in E)$. So, EV_i^n needs to solve an optimal energy buying problem (EBP) by computing an optimal bid price as follows:

$$EBP : \max_{B_i^n} [U_i(E_i^n) - pay_i(Bid_i^n)] \tag{4.8}$$

  where $pay_i(Bid_i^n)$ is the payment function of EV_i^n given by the auctioneer.

- **Service Providers:** The bid price vector of SP_j^n for selling energy on the blockchain network is denoted as $P_j^n = (p_{ji}^n | i \in E)$. The bid price matrix of the SP_j^n is $SP^n = (P_j^n | j \in Z)$. So, SP_j^n solves an optimal energy selling problem (ESP) by determining optimal bid price:

$$ESP : \max_{P_j^n} [Rew_j(P_j^n) - L_j(S_j^n)], \tag{4.9}$$

  where $Rew_j(P_j^n)$ is a reward function of SP_j^n given by the auctioneer.

Algorithm 7 Selection of the Service Provider

Input: N: The number of EV requests for charging the battery.
M: The number of SPs who have submitted bids for discharging the energy.
p_{ji}: represents the bids submitted by the SPs, where, i represents the bid for an i^{th} EV and j represents the SP_j.
Output: Selection of the SP_j used in energy trading for demand response management.

```
procedure FUNCTION($N, M$)
    for $(i = 1; i \leq N; i++)$ do
        Select the $EV_i$
        Submit the auction bid price $b_{ij}$ and required energy $E_i$ by $EV_i$ on the blockchain network
        for $(j = 1; j \leq M; j++)$ do
            Select the $SP_j$
            Submit the auction bid $p_{ji}$ by the $SP_j$ on the blockchain network
        end for
    end for
    if $(b_{ij} \geq p_{ji})$ then
        Calculate the Optimal_Prices for $EV_i$ and $SP_j$ as defined in Eqs. 4.15 and 4.16    ▷ By Auctioneer
        $Optimal\_P.Value_1$ is used as $pay_i(Bid_i^n)$ for $EV_i$
        $Optimal\_P.Value_2$ is used as $Rew_j(P_j^n)$ for $SP_j$
    else
        No energy trading for demand response management.
        EV sends an energy request again on the blockchain network for demand response management.
    end if
end procedure
```

- **Blockchain as an Auctioneer:** The auction bid prices are submitted by the EVs and the SPs to the blockchain network to perform a double auction mechanism. EVs and SPs solve their energy buying and selling problems, respectively to update the bid price vectors according to the auctioneer's newly calculated *Optimal_Prices* as demand and supply for EVs and the SPs, respectively. The blockchain network acts as an auctioneer by triggering the smart contracts on the nodes on the network. The auctioneer solves the allocation problem optimally 'OAP' to find the traded amount of energy as follows:

$$OAP : \max_{E^n, S^n} \sum_{i=1}^{I} \sum_{j=1}^{J} [b_{ij}^n ln e_{ij}^n - p_{ji}^n s_{ji}^n], \tag{4.10}$$

From Eq. 4.10, if the bid prices are known then, an auctioneer can solve the problem 'OAP'. Note that both Problems 'OAP' and 'SWP' have same subject to constraints as described in Eq. (4.4). So, here also we carry out constraint relaxation through Lagrangian method 'L_2'. To ensure that the optimal solution of one problem solves the other problem. Therefore, L_2 and L_1 have the same Lagrange multipliers as follows:

$$\begin{aligned}\nabla_{e_{ij}^n} L_2(E^n, S^n, \lambda, \beta, \alpha, \gamma, \theta) = \frac{b_{ij}^n}{e_{ij}^n} - \eta \lambda_i \\ + \eta \beta_i - \gamma_{ij} - \theta_{ij} = 0\end{aligned} \tag{4.11}$$

$$\begin{aligned}\nabla_{s_{ij}^n} L_2(E^n, S^n, \lambda, \beta, \alpha, \gamma, \theta) = -s_{ji}^n \\ + \alpha_j + \rho \gamma_{ij} = 0\end{aligned} \tag{4.12}$$

As the lagrangian multipliers are the same. Thus,from Eqs. (3.1), (3.2), (4.11), and (4.12), it is known that:

$$b_{ij}^n = \frac{\eta w_i e_{ij}^n}{(\eta \sum_{j=1}^J e_{ij}^n - e_i^{n,min}) + 1} \tag{4.13}$$

$$-s_{ji}^n = -2c_1 s_{ji}^n - c_2 \tag{4.14}$$

4.4.2 Optimal Prices for EVs and SPs

The optimal price values of the EVs and the SPs allocated by an auctioneer is defined as follows:

$$pay_i(Bid_i^n) = \sum_j^J b_{ij}^n \tag{4.15}$$

$$Rew_j(P_j^n) = \sum_i^I \frac{(p_{ji}^n)^2}{4c_1} \tag{4.16}$$

Now, we calculate the pricing rules of the EVs and the SPs.
From the Eq. (4.8), we calculate:

$$\frac{\partial U_i(E_i^n)}{\partial b_{ij}^n} - \frac{\partial pay_i(Bid_i^n)}{\partial b_{ij}^n} = 0 \tag{4.17}$$

Hence,

$$b_{ij}^n = \frac{\partial U_i(E_i^n)}{\partial e_{ij}^n} e_{ij}^n = \frac{\eta w_i e_{ij}^n}{(\eta \sum_{j=1}^J e_{ij}^n - e_i^{n,min}) + 1} \tag{4.18}$$

Similarly, From the Eq. (3.14), we calculate:

$$\frac{\partial Rew_j(S_j^n)}{\partial p_{ji}^n} - \frac{\partial L_j(S_j^n)}{\partial p_{ji}^n} = 0 \tag{4.19}$$

Hence,

$$s_{ji}^n = 2c_1 s_{ji}^n + c_2 \tag{4.20}$$

From the Eqs. (4.18) and (4.20) shows that the optimal price values mentioned in the Equations. (4.15) and (4.16) satisfy the Eqs. (4.13) and (4.14) and ensures optimality.

According to the proposed mechanism and Algorithm 7, the auction bid prices EVs and the SPs are stored on the blockchain network. By using these bid prices, the auctioneer solves 'OAP' to allocate the energy demand and supply. The auctioneer broadcasts a new prices solution to the EVs and the SPs. After that, they solve their own 'EBP' and 'ESP' problems to find optimal price for demand response management. Here, the termination condition is that the newest bid prices satisfy the convergence ξ condition (RCB $< \xi$ and RCS $< \xi$). If not, the algorithm repeatedly executes from the starting steps. EBP, ESP, and OAP can be solved through multiple iterations. Here, ξ determines the execution time and the accuracy of this algorithm. When ξ becomes small, the final approaches to the optimal values. More details on a double auction mechanism are given in Algorithm 8.

According to Eqs. (4.18) and (4.20), it is known that an EV and the SP will bid truthfully and maximize the utilities by solving EBP and ESP. Our proposed double auction satisfies the following properties:

Algorithm 8 Double Auction Mechanism

Input: ξ, η, SoC^n, θ
Output: E^n,S^n,Bid^n,P^n

```
procedure FUNCTION($DoubleAuctionMechanism$)
    Initialization: signal $\leftarrow$1, $k \leftarrow 0$, $Bid^{n(0)}$, $P^{n(0)}$
    while signal do
        if Participating EVs are not active or are not the nodes of the blockchain network then
            The auctioneer ends the process and arranges for Algorithm 2 to start again.
        else
            Using $Bid^{n(t)}$ and $P^{n(t)}$, Auctioneer $\xrightarrow{\text{solves}}$ Problem $OAP$ to get $E^{n(t)}$ and $S^{n(t)}$, and then announces the results to EVs and SPs, respectively.
            Based on $E^{n(t)}$ and $S^{n(t)}$, EVs $\xrightarrow[\text{optimal bid}]{\text{solves}}$ $Bid^{n(t+1)}$ through solving EBP, and acknowledge it to Auctioneer.
            Based on $E^{n(t)}$ and $S^{n(t)}$, SPs $\xrightarrow[\text{optimal bid}]{\text{solves}}$ $P^{n(t+1)}$ through solving ESP, and also acknowledge it to Auctioneer.
            $k \leftarrow k+1$
            if RCB $< \xi$ and RCS $< \xi$ then
                signal $\leftarrow$ 0
                $k \leftarrow k-1$
            end if
        end if
    end while
end procedure
```

1. **Individual Rationality (IR):** No node, *i.e.,* EVs and SPs in the blockchain network

should loose from joining the auction.

2. **Weak balanced budget (WBB):** The auctioneer should not lose money while performing the double auction mechanism.

3. **Economic efficiency (EE):** The social welfare should be the best possible after all energy trading in demand response management has completed.

The proposed double auction mechanism achieves an optimal energy trading solution in demand response management with social welfare maximization and privacy protection of EVs.

4.4.3 Demand Response Management

This subsection represents the energy transaction for demand response management between the EVs and the SPs on the network. In the blockchain network, all the authorized nodes need to audit and verify transactions and adds them in a new block by creating a consensus between them. It takes a certain time to finish the consensus process on the network. Then, the energy coins are transferred from the receiver's wallet address to the sender's wallet address. The step-wise detail description of energy trading transactions for demand response management between the requested EV and the selected SP is described as follows.

1. An EV EV_i (*i.e.,* energy buyer i with enough energy coins) make a request on a blockchain network to buy some amount of energy. Then, according to the price announces by the SPs, EV_i chooses the selected SP_i (,*i.e.,* energy seller i) using above-mentioned auction mechanism. Also. EV_i sends an energy request to a particular SP_i including the true identity 'ID_i', wallet address 'WID_i', current balance '$credit_i$', namely as in the following Eq. 4.21,

$$EV_i \rightarrow SP_i : request_i = ID_i||WID_i||credit_i \tag{4.21}$$

2. After requesting '$request_i$', the SP_i verifies the ID_i of an EV_i and check the funds in the given WID_i as per the requirements for energy trading transaction between them.

3. After the verification of EV_i by SP_i, it is allowed to obtain a token from the blockchain network for demand response management and fulfil the following demands.

    - There is enough wealth in EV_i's energy coin account or in a wallet address.
    - EV_i has a unique identity ID_i with an authenticated information. This ID_i of an EV_i should be in an encrypted form with its private key (PK_i) as mentioned in the following Eq. 4.22.

$$ID_i = PK_i(Header||Content) \tag{4.22}$$

- All the other nodes on the network verifies the ID_i = PK_i ($Header$ || $Content$) of an EV_i with its corresponding public key (PU_i). They calculate the $Verify_i$ = PU_i (ID_i). If the verification is true then, EV_i is an authenticated user otherwise not.

4. After the verification of EV_i, it receives a response '$response_i$' from the SP_i that includes token T_i and signature $SignToken_i$ as mentioned in the following Eq. 4.23.

$$\begin{aligned} SP_i \rightarrow EV_i : response_i \\ = T_i||SignToken_i||Timestamp \end{aligned} \tag{4.23}$$

   where as,
   T_i = $credit_i$ || t || pre_record_i || $Timestamp$
   pre_record_i = Hash (TX_i) where, i = 1,2,3...h
   Here, T_i includes $credit_i$ that represents the current balance of EV_i, t represents verification of an EV_i, pre_record_i represents the previous record of the energy trading transactions of an EV_i, and $Timestamp$. EV_i should pay energy coins as a reward to SP_i when the transaction would successfully completed between them.

5. Further, EV_i sends T_i to SP_i for demand response management (DR_i) between them as mentioned in Eq. 4.24.

$$\begin{aligned} EV_i \rightarrow SP_i : DR_i = \\ T_i||SignToken_i||Timestamp \end{aligned} \tag{4.24}$$

6. SP_i broadcasted the DR_i on the blockchain network (BN) with digital signatures on it. All the other nodes verifies the receiving T_i by comparing it with the original data present in the ledgers. If the T_i matches then, allow EV_i for demand response management otherwise not, as mentioned in the following Eq. 4.25.

$$\begin{aligned} SP_i \rightarrow BN : Verification\&Validation_i = \\ DR_i||SignToken_i||SignDR_i \end{aligned} \tag{4.25}$$

7. Then, the energy transaction between EV_i and SP_i for demand response management will started and payment as energy coins will be transferred to the SP_i's wallet address from the EV_i's wallet address.
   All the transaction information is audited and recorded in the ledgers of the blockchain, which can never be changed.

4.4.4 Complexity Analysis

4.4.4.1 Time Complexity

In Algorithm 7, the first *"for"* loop calculates b_{ij} for N number of EVs and the second *"for"* loop evaluates the p_{ji} run on blockchain for M number of CSs. The total time for both *"for"* loops is O(NM). The conditional operators used takes $O(1)$ time. Hence, the total computation time is of $O(NM) + O(1) = O(NM)$ in the worst case.

In Algorithm 8, the conditional operators take $O(1)$ time. The bids submitted by EVs and the SPs *,i.e.,* B^n and P^n, respectively on a blockchain and then, auctioneer solves the E^n and S^n, which takes total time is of $O(n)$. After, EVs compute B^n by solving EBP based on the auctioneer results that takes $O(n)$ time. Similarly, SPs compute S^n by solving ESP based on the auctioneer results that takes $O(n)$ time. Hence, the total computation time of this algorithm is of $O(1) + O(n) + O(n) + O(n) = O(n)$ in the worst case.

4.4.4.2 Space Complexity

In Algorithm 7, two lists are presented having N and M number of EVs and SPs, respectively. According to the insertion sort, these two lists take space complexity is of $O(NM)$. The rest of the algorithm takes $O(1)$ space that uses conditional operators. So, the total space complexity of this algorithm is of $O(NM) + O(1) = O(NM)$.

In Algorithm 8, the conditional operators take $O(1)$ space. To calculate the value of E^n and S^n by the auctioneer on the basis of B^n and P^n bids submitted by EVs and SPs, respectively take the space complexity is of $O(n)$. Hence, the total space complexity of this algorithm is of $O(1) + O(n) = O(n)$.

4.5 Performance Evaluation

In this section, we discuss the simulation results and security and privacy analysis of the proposed energy trading scheme for demand response management.

4.5.1 Numerical Settings

The performance of the proposed scheme is tested on a private Ethereum network. For simulation, we have considered a number of EV charging loads of 143 homes. The quantitative consumption data was supported by an online survey (83 respondents) and face to face interviews (13 respondents) with participants enrolled in the CLNR project based on a real dataset [231]. The charging energy demand of EVs range is [10, 60] KWh and the range of minimum price, EVs willing to buy the charging energy is [10, 60] units per KWh, whereas SPs range to discharge the energy is [50, 250] KWh with minimum selling price ranging from [5, 50] units per KWh. The cost factors used in the cost functions *,i.e.,* c_1 and c_2 is 0.01 and

0.015, respectively. The parameters η and ρ used in simulation are 0.8 and 0.9, respectively. η represents the average charging efficiency and ρ represents the average energy transmission efficiency. The threshold value of convergence ξ is 0.001.

4.5.2 Results and Discussion

The proposed scheme is compared with the existing state-of-the-art schemes [34, 169, 177, 220] and its performance is evaluated based on maximum social welfare, average converged iterations, scalability metrics: average throughput and latency, average buying and selling price, average transmitted and available energy, and standard deviation.

4.5.2.1 Impact on Social Welfare Maximization

Fig. 4.3 shows the convergence evolution of maximum social welfare achieved using Algorithm 8 in comparison to the existing algorithms discussed in [34,177]. Note that the maximum social welfare rapidly converges close to the optimal value, *i.e.,* after 10 iterations whereas in the existing schemes [34, 177] converges after 25 and 12 iterations, respectively. Similarly, Fig. 4.4 shows the iteration convergence comparison between Algorithm 8 used for demand response management and the P2P energy trading algorithms discussed in [34,169,177]. After 10,000 experiments of energy trading with different energy demands by EVs, the average converged iterations of Algorithm 8 is 11, which is less than that of 11.9 in [177], 12.774 in [169], which is 37.5% less in comparison to [34]. From Fig. 4.4, it is clear that our proposed energy trading scheme for demand response management is faster than the existing P2P energy trading schemes.

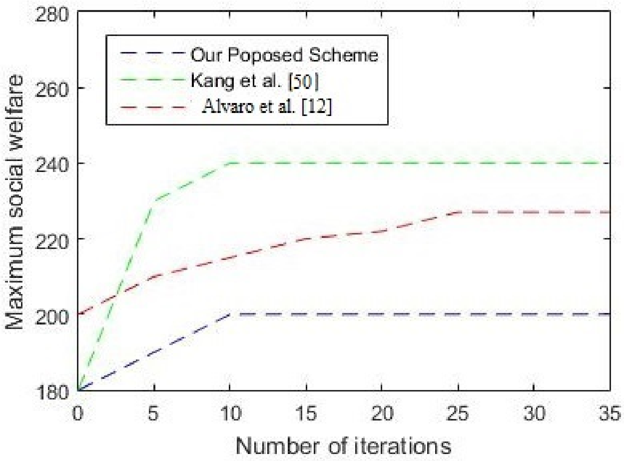


Figure 4.3: Comparison of evolution of maximum social welfare

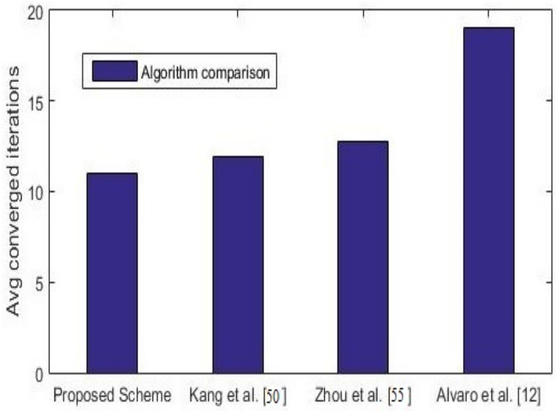


Figure 4.4: Comparison between different algorithms

4.5.2.2 Impact on Average Price and Amount of Energy

Fig. 4.5 shows the comparison between the proposed scheme and an existing energy trading scheme discussed in [177]. It clearly shows the comparison between average selling price and average buying price between the energy sellers and the energy buyers. In the existing scheme, authors described the electricity trading between the PHEVs. However, we focus on a P2P energy trading between EVs and the SPs. In addition, the proposed scheme achieves approximately 95% energy efficiency while trading or transmission whereas, the existing scheme in [177], the energy efficiency during electricity transmission is 90% approximately as mentioned in [232]. Similarly, the results in Fig. 4.6 shows that the proposed scheme in comparison to the existing scheme as discussed in [177] works better in transmitted energy to EVs and available energy at SPs. Hence, the proposed scheme has less energy loss and high energy utilization efficiency as compared to the existing trading scheme in [177].

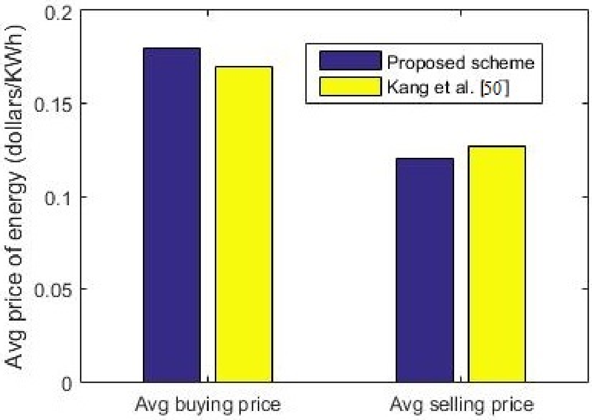


Figure 4.5: Comparison of average buying and selling price

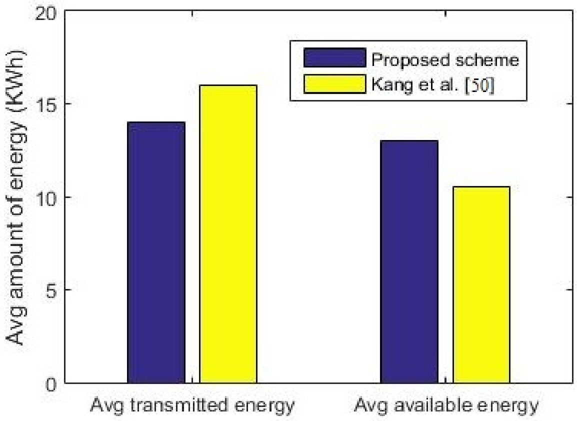


Figure 4.6: Comparison of transmitted and available energy

4.5.2.3 Impact on Scalability

In order to evaluate the scalability metrics of the system model, we analyze average throughput and latency of our trading platform for demand response management on a private Ethereum blockchain. For this, we conducted several experiments under different workloads and network sizes. Six types of workload are used by sending the transaction rate is 100, 200, 500, 700, 1000, and 1200 transactions/sec. A blockchain with 1, 2, 3,.. upto 25 sealers are studied as a network size. The block time between two consecutive blocks is fixed and set to 2 seconds. The total number of transactions to be sent is also fixed and set to 10,000 as simulation parameters.

Fig. 4.7 shows the average throughput of the different transaction sending rates versus number of sealers. For moderate rates; 100, 200 and 500 tx/sec, the system achieves max throughput with all the transactions get processed and added to blockchain. For higher rates such as 700, 1000, and 1200. tx/sec, the throughput is automatically affected by the number of sealers, when scaling up to 25 sealers and drops below 50% of a sending rate of 1200 tx/sec. Similarly, Fig. 4.8 shows the average latency, which is inversely proportional to the throughput. For a moderate sending rate of a network size, the average latency of the different transaction sending rates is between 2.3 and 3 seconds. However, a higher sending rate and a bigger network size cause the latency to increase significantly up to 12 seconds. Fig. 4.8 clearly shows that the delay grows for handling of higher transaction rates because more time is needed to propagate the corresponding volume of data to all the sealers. Results also show that the maximum throughput is 500 tx/sec that supports the implementation platform.

4.5.2.4 Impact on Block Numbers

To show the limited computation power impact on the network size and time of the block, we observed the number of transactions per block by sending different transaction rates such as 200, 500 and 1000 (Fig. 4.9, 4.10 4.11). As shown in Fig. 4.9, the transaction sending

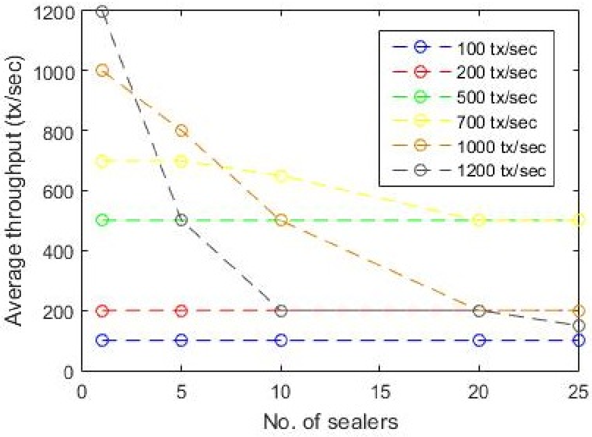


Figure 4.7: Average throughput versus number of sealers

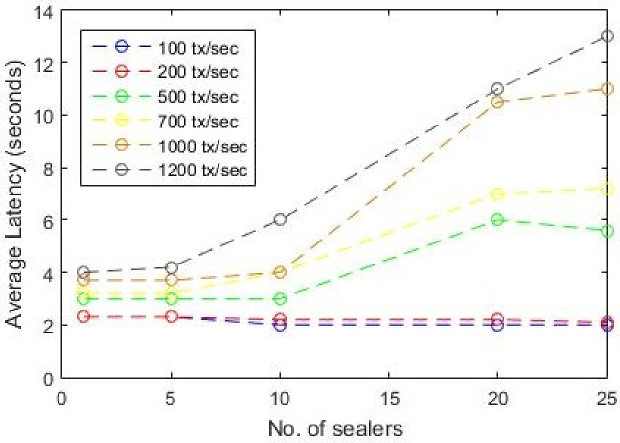
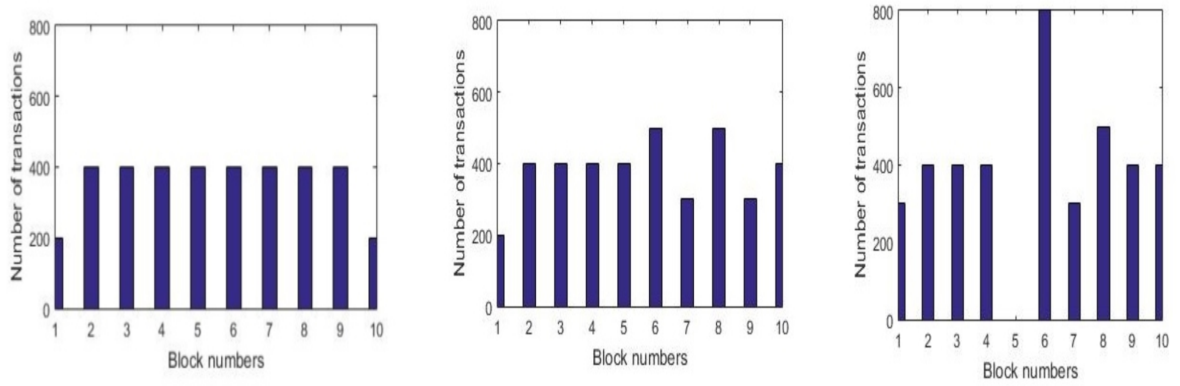


Figure 4.8: Average latency versus number of sealers

rate is 200 tx/sec with 5, 10, and 20 sealers in Fig. 4.9(a),(b),(c) respectively. In Fig. 4.9(a), most of blocks are generated with uniform size and receive the same number of transactions, which is equal to the maximum throughput in block time of 2 sec. However, with an increase in the number of sealers and the transaction sending rate, the block sizes become more and more irregular as shown in Fig. 4.9, 4.10 4.11. To confirm this irregulation with respect to the increase in the number of sealers and the transaction sending rate, we plot the standard deviation of block sizes in Fig. 4.12. It clearly shows that the deviation from the mean grows higher but this deviation is lesser than the existing energy trading scheme in [220]. However, the higher transaction sending rates incur delay in the process and affect the generation time of new blocks.

The comparison between the proposed energy trading scheme and the existing schemes in simulation results is as shown in Table 4.1.

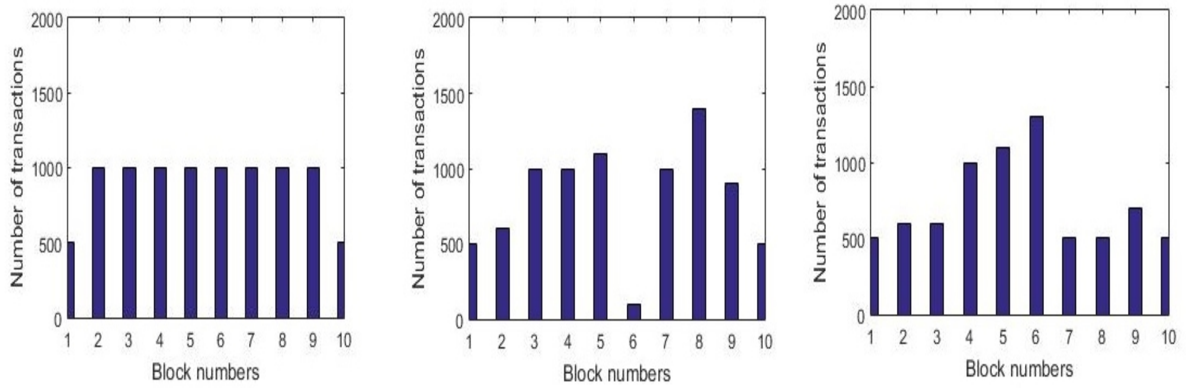


(a) 5 number of sealers

(b) 10 number of sealers

(c) 20 number of sealers

Figure 4.9: Number of transactions within each block having sending rate 200 transactions/sec

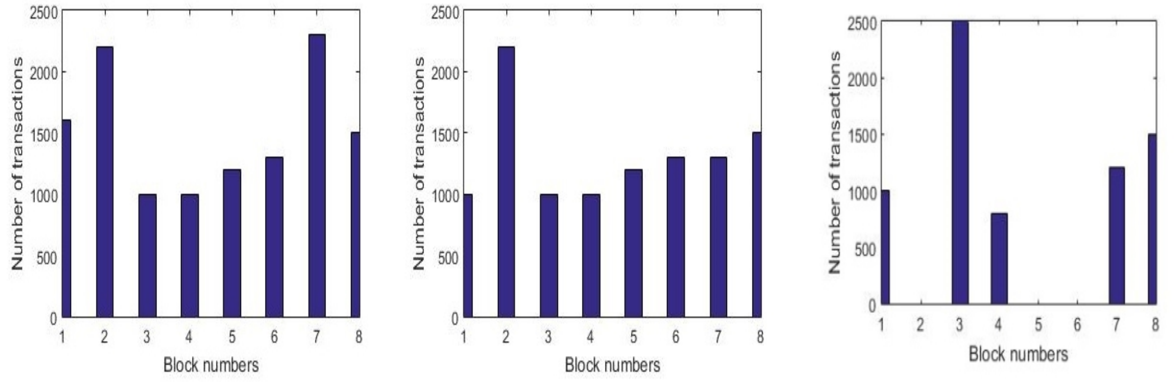


(a) 5 number of sealers

(b) 10 number of sealers

(c) 20 number of sealers

Figure 4.10: Number of transactions within each block having sending rate 500 transactions/sec



(a) 5 number of sealers

(b) 10 number of sealers

(c) 20 number of sealers

Figure 4.11: Number of transactions within each block having sending rate 1000 transactions/sec

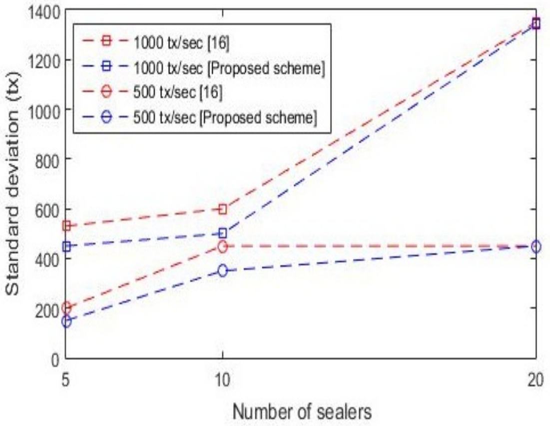


Figure 4.12: Comparison of standard deviation with transaction sending rates

Table 4.1: Comparison of simulation results of the proposed scheme with the existing schemes

Parameters	**Alvaro *et al.* [34]**	**Lasla *et al.* [220]**	**Kang *et al.* [177]**	**Zhou *et al.* [169]**	**Our Proposed Scheme**
Convergence reached	-	-	after 12 iterations	after 25 iterations	after 10 iterations
Average converged iterations	12.774 approx.	-	11.9 approx.	18.1 approx.	11 approx.
Maximum Throughput	-	350tx/sec	-	-	500tx/sec
Average latency	-	2.5-3.5seconds	-	-	2.3-3seconds
Standard deviation	-	600tx	-	-	450tx
Consensus Algorithm	-	PoA	Proof-of-Work	Proof-of-Work	PoA
Type of Blockchain	-	Private Blockchain	Consortium Blockchain	Consortium Blockchain	Consortium Private Blockchain

4.5.3 Privacy and Security Analysis

In this subsection, we have discussed the privacy and security analysis of the proposed scheme.

- **No trusted third-party:** The energy trading between the EVs and the SPs for demand response management has been done in a P2P manner. Thus, there is no need of third-party authenticator that makes the system more robust and scalable. We can also say that with the use of blockchain technology for demand response management in V2G environments, there is an elimination of trusted third-party.

- **Privacy protection:** To maximize the social welfare in V2G environments, we used double auction mechanism where EVs and SPs submit their prices on the blockchain network without any need of private information for energy trading known as *'Information Asym-*

Table 4.2: Privacy and Security analysis comparison of the proposed scheme with the existing schemes

Parameters	**Alvaro *et al.* [34]**	**Lasla *et al.* [220]**	**Kang *et al.* [177]**	**Zhou *et al.* [169]**	**Our Proposed Scheme**
Decentralized System	×	✓	✓	✓	✓
Privacy Protection	×	×	✓	✓	✓
Wallet Security	×	×	✓	×	✓
Transparency	×	✓	✓	✓	✓
51% attack	×	×	×	×	✓
Integrity	×	×	✓	✓	✓
DDoS	×	×	×	×	✓
Data Unforgeability	×	×	✓	×	✓
Transaction Authentication	×	✓	✓	✓	✓

metry'. The energy coin accounts of each node on the blockchain are pseudonymous that protect its identity privacy and account security. EVs prefer to use the public key for communicating with SPs rather than its true identity that prevents malicious attackers to hijack the private information of EVs.

- **Wallet security:** For the security of the wallet, the certification of the nodes is done using PKI infrastructure that provides the public and private keys to the nodes of a blockchain. Without knowing of corresponding keys and certificates, no-one can open a wallet of node and steal energy coins from the wallet on the blockchain network.

- **Transaction authentication:** All the energy transactions are validated and verified by an authority using PoA consensus in the proposed work. So, it is difficult for compromising all nodes due to the overwhelming cost of the blockchain network.

- **Data unforgeability:** The decentralized nature of consortium blockchain combined with cryptographic primitives ensures that an adversary cannot corrupt the energy transactions by taking the control over the blockchain system.

- **Integrity:** Once a block has been added into a blockchain, it includes the hash of the previous block, and its hash is stored in the next block. Therefore, it is difficult for a hacker to modify the block unless a hacker has a high amount of computational power. Moreover, the transactional data present in a block are secured by cryptographic primitives. So, it needs powerful resources to decrypt that data without knowing the private key.

- **Transparency:** Since the blockchain technology is DLT, so any participant node can have access to the blockchain and monitor the corresponding transactional data. Moreover, the transactional data is not saved on a single node and is transparent to all nodes. As a result, any malicious data modification can be traceable.

Hence, we have compared the proposed energy trading scheme with the existing schemes such as Alvaro *et al.* [34], Lasla *et al.* [220], Kang *et al.* [177], and Zhou *et al.* [169]. In Table 4.2, a comparison of the security features of above-mentioned schemes is listed. The comparison results show that the proposed scheme has better security features in comparison to the existing schemes.

4.6 Summary

The exponential growth of energy demand in industrial and residential areas may increase the burden on the smart grid in the years to come. Moreover, the use and evolution of EVs in V2G energy trading are likely to increase the energy load many folds on the smart grid. It may result in load fluctuations at the grid centre, causing undesirable instabilities. This behaviour's prime reason is the lack of security and privacy issues in a V2G environment. Hence, we proposed a consortium blockchain-based secure energy trading scheme for demand response management between EVs and the SPs to resolve these issues in V2G environments. In this chapter, we use a double auction mechanism between EVs and SPs to maximize social welfare. The blockchain network works as an auctioneer to conduct the auction according to their bid prices, which does not require private information about EVs. Numerical results based on a real-time implementation indicate that a double auction mechanism maximizes social welfare. Thus, the simulation results clearly show that the energy trading scheme for demand response management is practical enough to be incorporated in a V2G environment. Privacy and security analysis show that the proposed scheme improves transaction security and provides transparency in energy trading between EVs and the SPs. In the next chapter, we will discuss the conclusion of the research work.

Chapter 5

Conclusion and Future Scope

This chapter gives the concluding remarks on the research work related to applying blockchain technology in smart grid systems for managing the demand response. Moreover, it also discusses some open issues which can be taken as future works in these domains.

5.1 Conclusion

Blockchain is an emerging technology which consists of a chain of digital signatures in a cryptographic system. It provides security, integrity, confidentiality, AAA, and non-repudiation for real-time applications, which may not be provided by a centralized system efficiently. Therefore, it is one of the most powerful technologies to provide secure and dependable services to distributed smart communities like smart grids. Based on the existing challenges in smart grid systems, we reviewed and examined the energy trading mechanisms used in smart grid systems. Then, we reviewed a problem taxonomy on several typical models, such as incentive, mathematical, and simulation-based energy trading schemes. Especially, we mainly targeted the approved schemes in which energy trading mechanisms constitute various design challenges. Further, a solution taxonomy based on energy trading having enabling technologies such as SDN, energy internet, and blockchain has been discussed. Several unsolved issues were extracted from the literature review on energy trading between prosumers and consumers. Then, we provide a viable solution on an extensive view of SDN, Energy Internet, and blockchain, which may provide efficient and effective energy trading in smart grid systems. Based on the research findings on energy trading in smart grid systems, the research work focused on two problems: (i) an efficient incentive-based energy trading scheme between EVs and SPs, and (ii) a secure and decentralized demand response management scheme in smart grid systems. This task has been accomplished in the research work with two different approaches, game theory and auction theory.

In the first approach, an incentive-based PETS scheme has been proposed. This scheme is based on energy consumption real-time pricing using blockchain technology in smart grid systems. We have considered EVs to minimize their energy payment bills and SPs to maximize their profits. The interactions between EVs and the SP have been modelled using the Stackelberg game theory-based 1-leader, multi-followers, where SP_L is the leader, and *EVs* are followers. Firstly, we selected the leader among all SPs using a second-price reverse auction. Then, we used the Genetic algorithm to obtain the Stackelberg solution. The evaluation results show that the proposed PETS scheme outperforms the existing scheme with respect to the various performance evaluation metrics.

In the second approach, we have proposed a consortium blockchain-based secure energy trading scheme for demand response management between EVs and the SPs in a V2G environment. A double auction mechanism has been used between EVs and the SPs to maximize social welfare in this scheme. The blockchain network works as an auctioneer to conduct the auction according to their bid prices, which does not require private information about EVs. Numerical results based on a real-time implementation indicate that a double auction mechanism maximizes social welfare. Thus, the simulation results clearly show that the energy trading scheme for demand response management is practical enough to be incorporated in a V2G environment. Privacy and security analysis show that the proposed scheme improves transaction security and provides transparency in energy trading between EVs and the SPs.

5.2 Future Scope

The future research directions in the field of security and privacy in smart grid systems can be focused on the following aspects.

- To incorporate the big data handling techniques for analyzing the rapidly growing data and manage the load requirements in smart cities.
- A competitive energy market can be considered in the proposed PETS scheme. Then, the Stackelberg game model can be modified into a multi-leader, multi-follower game. Moreover, we can consider a multi-stage Stackelberg game, where EVs and SPs are the players.
- We can explore the resilience of the proposed demand response management scheme by increasing the workload and network size to analyze the network scalability.
- The efficacy of the proposed schemes can be tested by adding information about other parameters that are directly or indirectly related to the smart grid system.
- The effect of underlying communication architecture used like 5G and 6G can be studied on the performance of the proposed schemes.

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