Demand Side Management Using Blockchain for Peer-to-Peer Electric Vehicle Charging Networks

Master's thesis in Sustainable Energy Systems

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CHALMERS UNIVERSITY OF TECHNOLOGY

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Abstract

Electric vehicles (EV) are penetrating the consumer market at a rapid pace and remains an attractive alternative to fossil-fuel cars. Integrating a huge fleet of EVs in the existing grid infrastructure is challenging and expensive. Nevertheless, EVs provide an opportunity to tackle the growing renewable energy penetration since unused millions of EV's battery capacity can be used to shift loads in order to manage intermittency and peer-to-peer (P2P) energy trading services. A novel permissioned blockchain based EV charging framework with P2P energy trading services is proposed in this thesis. Within this framework, smart contracts are formulated to create proof-of-concept for decentralised P2P EV charging networks. Additionally, an optimal EV scheduling optimization using non-cooperative game theory is formulated to shift the peak demand and flatten the load demand curve. The proof of concept is validated through tests and has proven the technical feasibility of permissioned blockchain. With the implementation of a permissioned blockchain, users will be able to make use of the website and app designed in the thesis to shift peak loads as well as navigate prosumers. The goal of this permissioned blockchain network is to encourage users to make use of the sustainable energy whilst most available through an incentive-based energy trading system in order to reduce intermittency.

Keywords: Blockchain, Demand Side Management, Electric Vehicle, Game Theory, Peer-to-Peer, Smart Contract, Vehicle-to-Grid.

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Raghuvar Vijayakumar
& Shruthik Krishnan Muthukrishnan
Gothenburg, June 2021

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MPC Model Predictive Control
TLA Three Letter Acronym
DApps Decentralised Application
EVM Ethereum Virtual Machine
EV Electric Vehicle
DSM Demand Side Management
P2P Peer-to-Peer
TSO Transmission System Operator
DSO Distribution System Operator
kWh kilowatt-hours
RE Renewable Energy
SOC State-of-Charge
SOH State-of-Health
V2G Vehicle to Grid
PV Photo Voltaic
IoT Internet-of-Things
ICE Internal Combustion Engine
EE Energy Efficiency
DR Demand Response
SGAM Smart Grid Architecture Model
CEN European Committee for Standardisation
CENELEC European Committee for Electrotechnical Standardisation
ICT Information and Communication Technologies
DN Decentralized Network
V2H Vehicle-to-Home
V2B Vehicle-to-Building
ECDSA Elliptic Curve Digital Signature Algorithm
PoW Proof-of-Work
PoS Proof-of-Stake
OOPS Object Oriented Programming Language
DApps Decentralized Application
DoS Denial of Service

Introduction

The increasing demands for energy resources all around the world as well as the growing interests in sustainability in processes concerning the Paris Agreement have sparked significant interests in energy markets and trading. The power industry and transportation systems have been recognized as the major contributing sources of environmental pollution and CO2 emissions. The transportation sectors play an elementary role in the trading of goods, social, and economic development and are a major reason for urbanization in cities (García-Olivares et al. 2018). From a global perspective, transport-related energy consumption accounts for about one-third of the world's total energy consumption (W. Zhou et al. 2016). To tackle this issue, electric vehicles have gained popularity due to their capability to shift the world towards sustainable energy and particularly renewable power generation. The use of Electric Vehicles (EV) is becoming a mainstream consumer offering with more than 200 million electric cars and 900 million two-wheeler vehicles poised to run on roads by 2030 (IRENA 2019). However, there are also challenges pertaining to the EV industry. One such is the limited driving range of the vehicle with an average distance of 300km (Electric Vehicle Database 2020). The second weakness is related to the long charging hours required to charge the battery pack. A typical battery pack with a 60 kWh battery capacity could take up to 8 hours to charge with level 1 chargers at 7 kW rated power (Sassi and Oulamara 2017). The third limitation is the concerns with the development of charging infrastructure and the limited capacity of the electricity grid.

Blockchain networks can be implemented to influence the time of electric vehicle charging, leveraging the growing EV fleet to balance the energy management according to the building, and provides incentives to the customer for integrating to the system. Through Peer-to-peer energy sharing of the EV chargers in the building blockchain can enable timely transactions and enable the customer to have real-time information of the electricity cost. Blockchain-enabled charging solution allows the load to react on available renewable electricity/electricity price instead of the traditional way of altering the distribution to match the demand.

Aim

The aim of the thesis is to implement a blockchain energy sharing framework, and to enable Peer-to-Peer energy trading platform for electric vehicle charging networks using demand response strategies.

Objective and Research Scope

- Create a blockchain framework for P2P EV charging networks
- Formulate a game theoretic optimization model to balance the supply-demand equilibrium of the energy network
- Validate the blockchain framework using Solidity to deploy and develop smart contracts in Remix IDE

The thesis aims to establish the role of blockchain in future decentralised energy systems. As the energy system moves more towards the electrification, new challenges oppose the development of these systems. The main focus is on developing a blockchain framework for EV charging in a peer-to-peer network. The peer-to-peer entails different actors in the residential grid, who can buy and sell electricity in a decentralised market. Established a secure transaction network requires a lot of security and reliability. Blockchain-as-a-platform can help establish the connections and secure transactions between peers. Moreover, the data in the blockchain is stored in a decentralised structure rather than the traditional centralised method and the main advantage is the protection against malicious attacks. In the case of a centralised system, an attack on any of the peer nodes can destabilise the entire system. In the case of blockchain, data is stored in every peer and helps in the back-up of the system. Peer-to-peer energy trading using blockchain is simulated in a residential network with an EV aggregator managing EV charging from the grid. Three scenarios of how the EV could charge in P2P network are analysed through the blockchain framework and only the EV charging aspect is explored in the P2P energy network. Moreover, the only blockchain as a technology enabler is considered and studied. Alternate solutions enabling P2P are not explored nor compared.

Thesis Structure

The structure of the thesis is as follows:

Chapter 1, *Background*- The grid is experiencing a tremendous change as energy consuming technologies, EV's are introduced to the system. The model explains the transition of the electric power system to accommodate the growing fleet of EV by using demand side management strategies and game theoretic optimization approach to integrate blockchain interface and energy trading markets as drivers to mitigate climate change and shave demand peaks.

Chapter 2, *Smart Grids*- A smart grid is an electricity network enabling two-way flow of electricity and digital information. The smart grids are essential to transform the electricity network. DSM strategies are used to change the consumer energy consumption patterns thereby increasing energy efficiency in processes. The Smart Grid Architecture Model (SGAM), is a reference work developed to assist in building the smart grid architecture. A P2P model focused on distributed energy trading is optimized based on game theoretic, incentive driven, and cooperative approach. The model also introduces the use case of V2G charging to maintain the grid's energy demand during peak load hours.

Chapter 3, *Game Theory*- It enables the mathematical modeling of strategic interaction between two or more players in a scenario consisting of a set of rules and outcomes. The game-theoretic optimisation framework is a set of games which specify the following entities, the players in the game, the digital information, actions available to each player, and the pay-offs of each outcome. The game-theoretic formulation helps to achieve equilibrium to the game where each set of outcome occurs with known probability.

Chapter 4, *Blockchain Technology*- Blockchain technology provides a digital record of transactions implemented in a distributed fashion eliminating a central authority. This chapter further explains the architecture, structure, and benefits of the blockchain infrastructure. Solidity, a high level programming language is used to write smart contracts, it is developed and deployed on Remix interface.

Chapter 5, *Application of Blockchain in P2P Network*- This chapter discusses the various aspects of the application of blockchain interface to the smart grid network. It proposes a blockchain architecture to trade electricity, charge an electric vehicle, and track the energy data securely.

Chapter 6, *Methodology*- This chapter proposes a specific set of algorithms and procedures to develop and deploy the blockchain interface to study the dynamic behaviour of the modeled P2P network. The literature discusses the alternative methods and strategies to solve the rapid growth of electric vehicle demand and charging infrastructure using blockchain technology.

Chapter 7, *Analysis*- The chapter proposes a system modelled with a specific number of use case scenarios of a blockchain based energy trading system that analyze the PV production and the V2G capabilities to balance the grid's energy supply and demand. The study also proposes a third case scenario that works on the dynamic charging of the electric vehicle based on the price and demand peak of the electricity grid.

Chapter 8, *Conclusions*- This sections draws the main conclusions on the effect of demand side management strategies using a blockchain interface as a tool in a P2P network, specifically on the application of electric vehicle charging. Further extended scope and scale of the work is proposed.

1
Background

The introduction of EVs creates additional demand in the electricity grid. According to the study by Mckinsey 2018, electric vehicle adoption in Europe is projected to increase sharply, and the charging infrastructure will shift drastically from home charging to public charging in 2030. The total charging demand for electric vehicles is expected to by 2030, increase from approximately 4 billion kilowatt-hours to roughly 79 billion kilowatt-hours in the European Union alone. (Engel et al. 2018). Unlike traditional, internal combustion engines (ICE) vehicles, which only refuel at gas stations, EVs can recharge at multiple locations in multiple ways. This additional demand can be satisfied by the introduction of cost-effective and clean energy solutions such as solar and wind power energy generation by feeding into the grid. Also, this requires balancing the charging state of the vehicle in relation to the energy management of the building which is providing the service.

The electric grid is amid an exceptional shift as it integrates increased Renewable Energy (RE) into the system to mitigate energy shortage and climate change. Due to the intermittent nature of renewables, this remains a challenging task for grid operators. Vehicles that utilize electric powertrain as a propulsion system have shown promising development to reduce the cost of transportation as well as curbing emissions due to their battery storage systems which can be flexibly recharged at home (Ipakchi and Albuyeh 2009). This puts enormous loads on the grid and therefore, the capacity of the system must be increased. Grid expansion costs are expensive which does not translate to a sustainable future with the inclusion of electric vehicles. Consequently, the diversification of the power system towards renewable energy sources could contribute to the alleviation of energy security concerns in Europe (Battaglini et al. 2012). Especially in Sweden, a study conducted by AFRY 2010 shows dramatic implications of grid constraints and up to 150 billion SEK (Swedisk Crowns) in socio-economic losses. An EV aggregator or Distributed System Operator (DSO) is required to decide the control sequence of the EV charging based on technical constraints (e.g., State-of-Charge of battery, battery degradation) and specific objectives (e.g., reducing the price of charging). The involvement of the aggregator would maximise customer convenience (Shimizu et al. 2010) and reduce peak power demand from the grid (Sortomme and El-Sharkawi 2011).

In addition to increasing the need for renewables, electric mobility could emerge as an important source of storage for distributed energy resources (Andersen et al. 2019). The stored energy can be used in the context of Vehicle-to-Grid (V2G) charging. The stored energy in the battery serves as an energy source to send electricity back to the grid to facilitate load shifting to shave the demand peaks. The goal of the V2G charging is to decide whether the EV would complement the Peer-to-Peer network to charge, discharge, or provide frequency regulation at specific hours (Sassi and Oulamara 2017). Uncontrolled Electric Vehicle charging in low voltage distribution systems can result in considerable voltage fluctuations (Gruosso 2016). Therefore, the overall effect of electric vehicle charging on distributed nexus of systems shall be challenging and one of the most intriguing topics to explore (Gruosso and Bandeira 2017).

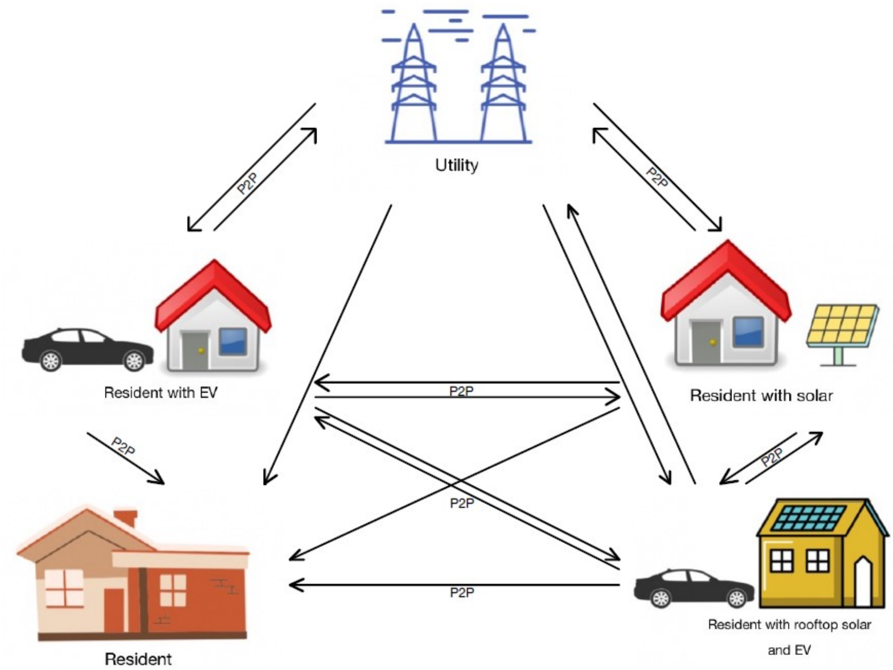

Figure 1.1: P2P structure (Y. Liu et al. 2019)

In this paper, we propose a series of secure, safe, and automated decentralized energy trading interfaces within a P2P network using smart contracts in blockchain technology. The Blockchain network is implemented to influence the electric vehicle charging, leverage the growing EV fleet to balance the energy demands according to the network, and provide an incentive to customers to integrate into the system. The blockchain-based energy trading system acts as a control center in which energy deals are processed, governed, and traded (Gai et al. 2019). Figure 1.1, represents the structure of a P2P network based on a permissioned blockchain with participants approved by the network owner. The system is self-sufficient and compliments the existing power system. Each node in the system is categorized into a consumer that needs the energy to satisfy the charging demand and prosumers with a photo-voltaic or V2G system capable of transferring energy to the electric vehicle. Each node consists of an IoT device, a smart meter that can store and monitor the purchased and produced energy. The smart meter conducts energy trading based on pre-programmed smart contracts within the blockchain network.

Table 1.1: Traditional vs Blockchain approach.

	Blockchain Approach	**Traditional Approach**
Single Point of Failure	No	Yes
Energy Profile Anonymity	Yes	No
Payment System	P2P Sales/Purchase System	Centralized
Authority	Decentralized	Centralized
Architecture	Peer-to-Peer Network	Client-Server Model
User Registration	Permissioned	Private

2

Smart Grids

The advancement in energy production and network technology, e.g., solar energy and smart grid, makes it possible for consumers to store, share, and trade energy (Maharjan et al. 2013). Smart Grid is an electricity network expected to monitor the consumption and enable the use of the two-way flow of electricity and information using digital communication technologies in real time between power suppliers and consumers to create a distributed energy trading network (Kang et al. 2018). Controlling and influencing the supply and consumption of electricity can shave the overall peak load demand, reshape the demand profile, and increase the sustainability in the grid by reducing emission levels and system costs. Demand Side Management is an important function that provides support towards electricity market control, management of decentralized energy resources, and electric vehicle charging infrastructure (Cohen and C. C. Wang 1988).

2.1 Demand Side Management

Demand Side Management (DSM) is used to refer to modifications made at the consumer's end to change their electricity consumption pattern by efficient use of energy and management of load. In the energy sector, DSM focuses on reducing the demand for electricity and energy sources by planning, implementing, and monitoring electric activities especially during peak hours (Singh et al. 2017). With the advancement in smart grids and the electricity market, DSM is classified into two main activities: Energy Efficiency (EE) and Demand Response (DR) (Behrangrad 2015). Energy efficiency involves a reduction in energy demand by using energy-efficient appliances. While Demand Response is often described as a reactive or preventative method to reduce, flatten, or shift demand in electrical energy usage by end-use customers compared to their normal consumption patterns. Figure 3.1, represents the advantages of demand-side management strategies to help manage the variations in the electricity system. Given the multiple benefits, emission reduction and conservation of resources from DSM, it is highly likely that implementing

DSM strategies in the P2P system would play an important role in transitioning to a sustainable network. Therefore, it is important to optimize the various load management strategies (Abaravicius and Pyrko 2006).

With the increasing share of renewable energy resources in the grid, coordination between the system operators is necessary. In general, there are two main operators in the system to provide flexibility, Transmission System Operator (TSO) and Distribution System Operator (DSO). The TSO's are an entity in charge of transmitting electrical power from the generation plants to the grids on a national or regional level (usually with output current varying between 220 kV and 380 kV in Europe) (Almassalkhi and Hiskens 2015). While DSO's are usually the operating managers of energy distribution systems, they play an important part in the demand response mechanism. The core functionality of the DSO's is to maintain the security of supply and quality of service.

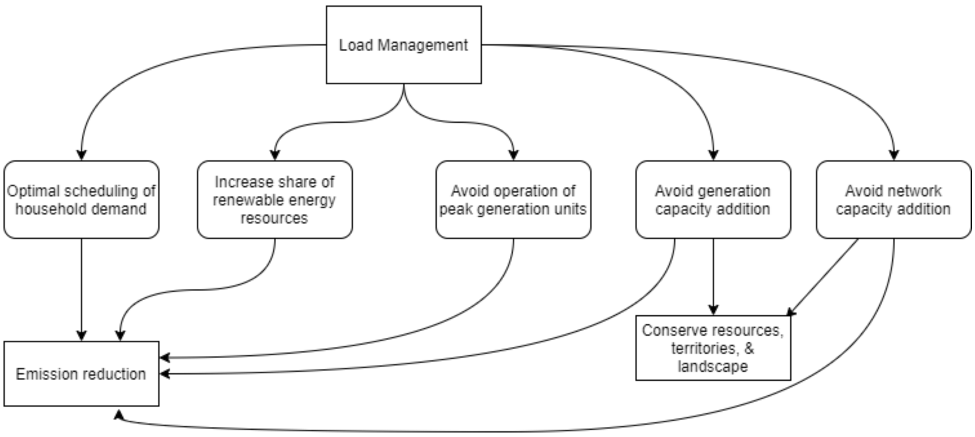

Figure 2.1: Advantages of Demand Side Management in Energy Systems (Abaravicius and Pyrko 2006)

2.1.1 Congestion Management

TSO is responsible for up-regulation and down-regulation of the power system by leveraging the balance power market with few producers. When the demand in the system is more than the scheduled amount then TSO has to perform up-regulation, where ancillary service providers provide additional power to keep the frequency at 50hz. When the demand in the system is less than the scheduled amount then TSO has to perform down-regulation, where the frequency is controlled to not raise above 50hz. In a real case scenario, the actual purchase of electricity occurs before the actual hour of consumption. Retailer bids a certain quantity of energy from the producer for the day-ahead market and the producer also sends the bids for selling the produced energy. If the retailer's estimated demand for the day ahead is less than the actual demand, then this additional electricity demand is settled by the TSO using up-regulating price. If there is overproduction in the total system power balance, the retailer gets a down-regulating price from the TSO. From a retailer's perspective, to maximize their profits, they need to optimally meet the system demand as deviating from the actual demand results in financial losses (Gerard et al. 2018). To guarantee a secure, reliable, and economical energy system, coordination between the TSO and DSO is deemed necessary.

2.2 Smart Grid Architecture Model (SGAM)

SGAM was proposed by European Committee for Standardisation (CEN) and European Committee for Electrotechnical Standardisation (CENELEC) to facilitate the development of smart grids. SGAM is intended to present a reference architecture and to provide methodological guidelines for technical groups to develop smart grids. Since the development of the smart grid introduces various new stakeholders, new applications and networks, especially Information and Communication Technologies (ICT). Introducing ICT into smart grids opens up various applications to be interlinked, especially like demand-side management of EV charging using peak shifting and V2G.

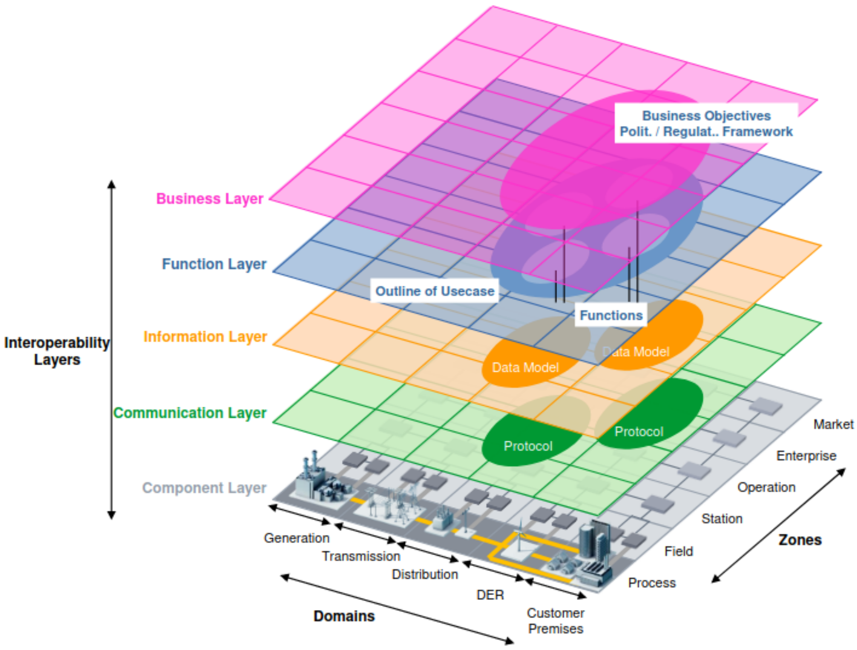

Figure 2.2: Smart Grid Reference Architecture(CEN-CENELEC-ETSI 2012)

The framework consists of five layers:

- Business layer: Maps regulatory and economic structures and policies.
- Function layer: Describes the functions and services offered in the smart grid.
- Information layer: Describes the information flow between functions, services and components.
- Communication layer: Establishes the protocol and mechanisms for the exchange of information between all entities.
- Component layer: Describes the physical distribution of all the participating components in the smart grid.

Inter-portability is the key enabler of smart grids. The term inter-portability means the ability of two or more entities to connect and exchange information and to utilize that correct information for correct operation.

2.3 Peer-to-Peer Energy Trading

Peer-to-Peer (P2P) energy trading in the grid enables the buying and selling of locally generated energy between residential, commercial, and business entities. The deployment of P2P trading leads to an increase in the distributed energy resources and flexibility in the grid. The P2P energy trading will transform the conventional consumers from passive to active managers of their networks (Aznavi et al. 2020). These active managers are often called prosumers based on their comprehensive capabilities of energy production, storage, and consumption. The prosumers sell the surplus energy to peers at a tariff specified by the utility back to the grid, while the consumers could buy the locally generated renewable energy at a cheaper price. The peer-to-peer energy markets play an important role as a decentralized platform to regulate the trade of electricity between the consumers and the producers. Implementation of P2P trading platforms enables better energy management to facilitate a balance between local demand and supply (IRENA 2020). The P2P energy trading scheme enables interested customers to buy electricity at a lower tariff from a peer during excess penetration of renewable energy sources. This decreases the customer's dependence on the electricity grid and the investments related to grid capacity needed to manage the peak demand. To enable peer-to-peer energy trading in the retail electricity market a decentralized platform, a blockchain framework is needed.

Peer-to-Peer Decentralized Network (P2PDN) is an energy exchange platform where different players in the system can exchange power with each other in a peer-to-peer manner. P2P energy trading is an upcoming distributed network that arises due to the high penetration of renewable energy sources with decreasing Feed-in-tariffs. P2PDN consists of players such as prosumers, consumers, micro-grids and utility grid. Designing a standard model for a peer-to-peer energy trading platform is a challenge due to a multitude of factors to weigh in during the decision making process.

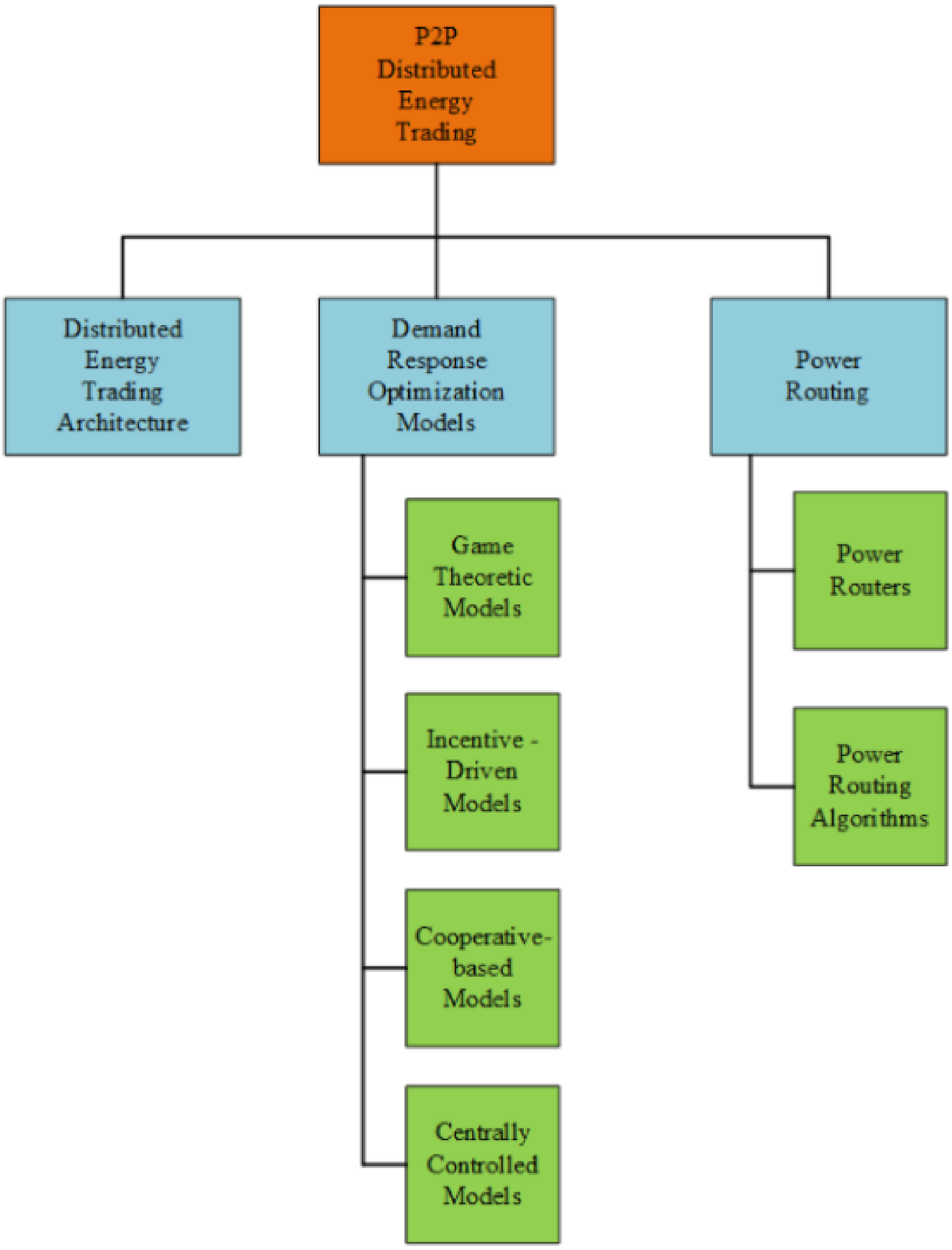

Figure 2.3: P2P Distributed Energy Trading (Abdella and Shuaib 2018)

2.3.1 Demand Response Optimization Models

Customer electricity demand is stochastic by nature, especially when considering the charging of electric vehicles. Failing to address this variation in the energy system results in peak load that causes frequency disturbances (Abdella and Shuaib 2018). Utility companies address this issue by reducing the peaks by using stored energy from an off-peak hour and it is a straightforward approach. Different techniques can be implemented to alleviate the peak loads and maintain a balance. The most common technique is to either use stored energy collected during off-peak hours or to adjust the operation of power generating units to generate/absorb extra power. The results of this approach however may lead to large operational cost and low efficiency as a result of under-utilisation (Abdella and Shuaib 2018). Power companies, therefore, attempt to maintain the balance between supply and demand vis-à-vis price-based optimisations and load scheduling. Load scheduling refers to the planning and calculation of the customers' consumption at certain times. This is performed either by the utility company or the customer. Load scheduling may be achieved through various methods; interruptible load, DLR direct load control (manipulating customer appliances) and DSB demand-side bidding (customer is allowed to prepare a bid). The customer is often incentivised based on price optimisation methods in which customers are incentivised to consume during off-peak times as a result of high price rates during peak hours (Abdella and Shuaib 2018). Load scheduling becomes more complex in a distributed power system as power is generated and injected into the system in a decentralized manner through various distributed energy sources (Abdella and Shuaib 2018). It is important to note that power generation from distributed renewable energy sources are inherently highly unpredictable as it depends largely on weather conditions as with wind and solar energy. It is for this reason that it is incredibly difficult to predict the amount of energy produced, sold and consumed. It is thus essential to make use of better methods of energy scheduling and price optimization such as incentive-based models (Abdella and Shuaib 2018).

2.3.1.1 Game Theoretic Models

The game-theoretic approach is the most widely employed method for demand response mechanism in the energy market. Mondal and Misra 2015 proposed a non-cooperative Stackelberg game based energy trading model for energy trading between Plugin Hybrid Electric Vehicle (PHEV) and microgrids. In this model, the PHEV decides the optimal energy demand whereas the grid sets the price of the energy. The model acts as a generalized version of a verified optimal nash equilibrium. The study proposed by Huiwei Wang et al. 2016, consists of an energy market framework to determine the nash equilibrium for energy trading among several peers connected through a central authority. The model with a single central authority enables the exchange of information in a private trading platform. The model is based on reinforcement learning and the Stackelberg game to trade energy between peers. Energy and payoff are shared among consumer and producer respectively according to their contribution to the energy market. According to the proportion of the demand and supply, the central authority calculates the amount of energy traded. The author Yaagoubi and Mouftah 2017 proposed a game-theoretic approach that allowed consumers to buy energy from neighbouring peers at a lower price than the utility. The seller decides the price and the consumers play a game to select the optimal seller to reduce the electricity price. The selection is performed based on the electricity price and the transmission cost from the grid to the consumer. The proposed model resulted in the minimization of the consumer's electricity bill and an increase in sellers profit. The simulated model gives a near-optimal solution. The model proposed by the author Samadi et al. 2015 works on the interaction between the prosumer that competes to sell their energy to the peers. Simulation results from the model showed that the prosumer can sell their excess energy to the local consumer at a higher price and the consumer buys the electricity at a cheaper price than the selling price of the utility.

2.3.1.2 Incentive Driven Models

The incentive-based model encourages the peers by providing an incentive-based motivation to continually participate and contribute to the energy trade network. The author (Huangxin Wang et al. 2015) proposes an incentive-based renewable energy trading mechanism that enables producers with surplus energy to trade with other peers who need it at the current hour, and vice versa to maximize the efficiency of surplus green energy production. The proposed method enables multiple users to trade energy simultaneously governed by a grid operator. The grid operator, in turn, coordinates the supply and demand energy profile by providing an infrastructure for energy routing. Another study (K. Zhang et al. 2016) classifies incentive-based demand-side strategy into four groups; pricing, bargaining, auctioning, and contract theories. The proposed study simulated a cloud-based Vehicle-to-Vehicle energy trading framework and optimal contract-based electricity buying scene to reduce transmission cost and maximize energy efficiency.

2.3.1.3 Cooperative Based Models

The Cooperative based model relies on consensus between multiple prosumers and consumers for mutual revenue gains. The study (Wu, Sun, et al. 2014) proposed a cooperative distributed energy trading model that involves prosumers with energy storage capabilities to trade energy in a cooperative approach to minimize the energy trading cost while satisfying the system demand. The algorithm is based on finding an optimal energy schedule that minimizes the energy-provisioning cost for the prosumer and an optimal transaction cost is determined to benefit the users registered in the energy network. (**s**)

2.3.1.4 Centrally Controlled Models

Centrally controlled models involve a central authority that intermediates between the prosumers and consumers. The study by author (Wu, Tan, et al. 2015), simulates a pricing based optimization formulation for a local smart-grid energy trading network. A local EV aggregator sets the cost of the electricity, a price lower than the utility company (DSO) set price to benefit the local P2P network. This model focuses on maximizing the profit of all the stakeholders involved.

2.4 Vehicle-to-Grid

V2G technology is the process of enabling controlled and bi-directional flow of stored electrical energy from the battery of an electric vehicle back into the power grid. Integrating the V2G system into the electricity network helps boost the grid's energy supply to manage the peak demand (Kempton and Tomić 2005). V2G technology also helps to curtail the surplus renewable energy production and mitigate climate change by storing the abundant and cost-effective energy produced in batteries (Clement-Nyns et al. 2011). As a peer in the P2P network, the battery can be used to charge and discharge based on different signals, such as energy production or consumption nearby. Subsets of V2G technology includes Vehicle-to-Home (V2H) charging which satisfies the household demand and Vehicle-to-Building (V2B) charging where the vehicle provides electricity to the commercial building. Alternatively, during power outages and blackouts V2G technology can be used as an emergency backup power unit (Briones et al. 2012).

3

Game Theory

Dutta and Dutta 1999 defined Game theory as "A formal way to analyze the interaction among a group of rational agents who behave strategically". In the above definition, the term 'group' refers to more than one decision-maker in the system and each decision-maker is called a player. 'Interaction' refers to how one player affects at least another player in the system. 'Strategic' refers to the player's individual preferences as to which action one decides to take. While 'rational' refers to the pre-notion that each player always chooses the best action to reach the best outcome for oneself.

A game is an activity where players compete against each other within the set boundaries. It is a set of strategic choices that each player makes against the other, that also includes the constraints. The game theory makes us comprehend how players within a system interact and the decision-making processes. Similar to other sciences, the game theory contains multiple models which can be used to solve a given problem. An abstract of real-world experiences and observations is termed a model. Though the complete meaning of the term model is loosely defined, it can accommodate vast relationships between situations, and across a wide range of problems (Osborne et al. 2004).

The game theory contains analytical tools developed to understand the phenomenon of how decision-makers interact in the system. The basic assumption of the players in the model are rational and pursue well-defined objectives that benefit the players themselves. Game theory models are abstractions of real-world cases that depict the (Osborne and Rubinstein 1994). The abstraction makes it unique to study different phenomena.

Game theory studies the interaction and co-operations between several parties using mathematical models. The broad definition of game theory is very helpful in utilizing it in many applications, ranging from warfare to economic strategies, from gambling to a nation's voting system. Game theory is an official mathematical discipline under American Mathematical Society Classification code 91A, but it has been mostly extended and developed by economists (Peters 2015).

3.1 Games in Normal form

A game has standard procedural representation, which can be represented in two ways, namely, extensive form and strategic form.

3.1.1 Rules of the game

Five main pre-requisites defines the game's outline

- The players who strategically interact in the game
- The number of strategies and choices with which each player plays the game
- In which order does each player gets to play
- The profit and losses from the strategic choices being made in the game
- Every player knows the rules of the game

3.1.2 Types of Game theory models

Figure 3.1, shows different types of game theory models broadly classified into 5 categories.

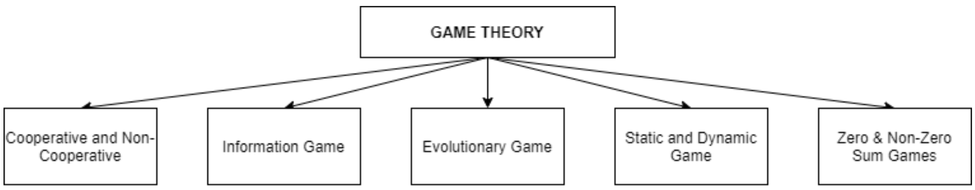

Figure 3.1: Classification of game theory models

3.1.2.1 Co-operative and Non-cooperative Game theory

Co-ordination between players forms the first basis of classification. There exists one strategy that yields maximum payoff for each player for each game. In certain cases, users co-operate to attain a better pay-off and this is termed as co-operative game theory. A tertiary player overlooks the game and assists the co-operation between the participants either by incentives or pre-written contracts. Players in a cooperative game theory have the motivation to participate due to the incentive mechanism and the resulting increased pay-offs from the interaction. On the contrary, the non-cooperative game model is formulated on the basis that there is no interaction or coordination between players to achieve a better pay-off. In this model, a player yields high profit by choosing the strategy which maximises ones' pay-off. Difference between the co-operative and non-cooperative game theory that the player coordinates with other players in the former, whereas the player acts in their self-interest in the latter. (Kreps et al. 1982)

3.1.2.2 Information Games

Information games are further divided into types of games namely, perfect information and imperfect information games. In perfect information games, each player knows the previous strategies used by all players. In a perfect information game model, only one player can move at that time instance by analyzing the motion of the other players (Yıldız 2011). Also, in this form of the game, the payoffs and strategies of all players at all instance of time are known to all players, i.e., a player who is about to make the move knows all the previous decisions made by all other users and also the consequence of current strategy that the player decides to make. On the other hand, in an imperfect game model, the player is not aware of other players pay-offs and strategies, and each player withholds private information which is unknown to other players in the game. (Nowak et al. 2000)

3.1.2.3 Evolutionary Game theory

Evolutionary Game theory analyzes the behaviour of large populations who interact repeatedly. Evolutionary game theory is founded by a mathematical biologist John Maynard Smith. Smith developed the traditional game theory method and incorporated the behaviour of rational economic agents into biological natural selection. The majority of the work in this field was undertaken by biologists and economists and applied to different disciplines like transportation, computer science, and sociology (Sandholm 2020).

The evolutionary game theory when merged with the basics of Darwinism accommodates the concept of time evolution, which lacks in the game theory that predominantly deals with the equilibrium. During the 1990s, multi-agent game simulations propelled the evolutionary game theory enabling the creation of a model which is more adaptable to real-world simulations (Tanimoto 2015).

In evolutionary game theory, the player's behaviour and outcomes are unique. This game theory decides how a state variable of a model changes over time. The reason behind the changes can be due to the phenomenon of survival of the fittest, imitations, or the optimization arising as the result of induced constraints (Newton 2018).

3.1.2.4 Static and Dynamic Games

In a static game, players make decisions simultaneously without the knowledge of what the other players are choosing to play. In the case of dynamic games, either the game is played sequentially or the game is repeated. In sequential games, players tend to opt for long term big pay-offs than short term small pay-offs. Also, players tend to make decisions based on how other players are choosing to play the game and predict the outcome of the game. (Hart 1992)

3.1.2.5 Zero Sum and Non-Zero-Sum Games

In Zero-sum games, the payoffs of one player affect the payoffs of the rest of the players. If one player gains profit by choosing a particular strategy, another player loses their payoffs, thereby the sum of all payoffs of all players in a zero-sum game tend to be zero. Moreover, each person's self-interest puts other person pay-offs at risk and thereby this type of game model is strictly competitive and also there is no cooperativeness among the players. However, if the sum of all payoffs of all players does not tend to zero, it is called non-zero-sum games. Here, people can be both co-operative or non-cooperative to get higher payoffs and this is termed as mixed strategies. In mixed strategies, a player chooses different strategies according to what the player believes would bring the better payoffs and one player's payoff does not necessarily result in the other's loss. (Moulin and Vial 1978)

3.1.3 Sets and Strategies

Strategic form: Encompasses the complete set of players, and the strategies available to each of them.

3.1.3.1 Strategic form or normal form games

A strategic form game is defined by 3 parameters.

- Number of players in the game
- Number of strategies available to each player
- Relative payoffs to each strategy played by each player.

3.1.4 Solution concepts for non-cooperative games

The main objective of a game is to predict how players are going to react to a given situation in the game (Aguirre 2008).

N: Players in the Game, N = {1 , ... ,n} S_i: set of strategies for player i $s_i \in S_i$: A strategy of player i $s_{-i} \in S_{-i}$: A strategy or set of strategies for other players other than player i. $u_i(s_i, s_{-i})$: payoff or utility of player i's in relation to the set of strategies $s \equiv (s_1,s_2,...,s_n) \equiv (s_i,s_{-i})$

3.1.4.1 Strategic Dominance

Strategic dominance is a state in game theory that occurs when a strategy that a user can use leads to better outcomes for them than alternative strategies. Dominant strategy and dominated strategy are two important terms that are crucial to the understanding of game theory. A dominant strategy is classified into two types, strictly dominant and weakly dominant. Where strictly dominant gives higher pay-offs than every other alternative strategy while a weakly dominant strategy leads to an equal or higher outcome than every other alternative strategy regardless of what other player chooses to play. Similarly, dominated strategy leads to a worse outcome for a user than other available strategies. Dominated strategies are also classified into strictly dominated and weakly dominated (Straffin Jr 1993).

3.1.5 Non-cooperative Game Theory

Non-cooperative game theory is a type of optimization modelling where a player's payoff depends on the strategies of the other players. An interesting aspect of non-cooperative game theory is that each player should anticipate the other player's strategy, make an assumption that every player is rational and try to make the most profit by maximizing the utility function. (Fudenberg and Tirole 1989). A fundamental characteristic of the non-cooperative game model is that the players in the game cannot form coalition and sign contracts beforehand. Co-operation among players can only stem from each user maximizing their payoffs. Non-cooperative game theory helps model economic problems where multiple players are presently characterized by strategic inter-dependency.

3.2 Nash Equilibrium

Invented by John Nash, Nash Equilibrium is a state where the game with a finite number of players and strategies has at least one mixed equilibrium. Nash equilibrium is the most popular solution for strategic form games. For example, if strategy A is getting dominated by strategy B, it is never a good option to play strategy A regardless of what the other player plays. Because strategy B always yields a better pay-off than A in all the scenarios. The following is a strict strategic game to demonstrate the existence of Nash equilibrium in a game.

Consider a game of N players, N={1,2, ..., i,... N} where each player $i \in N$ (i belongs to

N), and each player i has a set of strategies S_i={s_1,s_2,s_3 .., s_i, ... S_i} where $s_i \in S_i$. Here, S is a set of strategies available for each user i to play the game. For every strategy s_i played by the user i, there exists a payoff U_i. If s_i is the strategy played by the user i, s_-i is the set of strategies played by other players other than player i. By comparison, the payoff function for user i playing the strategy s_i is given by $u_i(s_i^*, s_-^* i)$. Let s_i^* be the strategy that yields the maximum payoff regardless of what the other players choose to play their strategy. Therefore, $u_i(s_i^*)$ will always be the maximum no matter what the other players choosing to play.

$$u_i(s^*{}_i, s^*_{-i}) \geq u_i(s_i, s^*_{-i}), s_{-i} = (s)_{j \in N} \tag{3.1}$$

Another way to define the Nash equilibrium is that S_i^* is the solution for $\max_{s_i \in S_i}$ $u_i(S_i, s^*{}_{-i})$ for every user. Eq 3.1 and the above explanation gives the Nash equilibrium for the strategic form game. It shows that the payoff for the players deviating from the strategy diminishes and there is no incentive to play other strategies which yield fewer profits.

Alpcan and Pavel 2009 investigated the optimization perspective of Nash equilibrium and discuss how game theory has been found to have immense potential in optimization, networking and distributed control. Additionally, the game theory could help quantify people needs and incorporate incentive paradigms and Nash equilibrium to suit the player's preferences.

3.2.1 Backward Induction

One of the important concepts in game theory is backward induction. Backward induction is the concept of working the problem backwards in time, going in a sequence of steps from the final part of the problem to the beginning. By analyzing the last portion of the decision-making, we can find out what's the best action to be performed at that moment. By this method, one can find out what the second-to-last decision should be and optimized accordingly (Aumann 1995).

4

Blockchain

Over the last decade, the use of blockchain has become increasingly popular in a variety of businesses. Many associate blockchain with the popular cryptocurrency Bitcoin. Blockchain was developed primarily due to a great need for a secure system that is efficient, reliable as well as cost-effective to conduct and record financial transactions (Gupta and Sadoghi, 2017:3). There is no singular concise agreed-upon definition of blockchain, however blockchain at its core can be understood as a "peer-to-peer distributed ledger that is cryptographically secure, append-only, immutable (extremely hard to change), and updateable only via consensus or agreement among peers" (Bashir, 2017).

Blockchain is a digital record of transactions implemented in a distributed fashion eliminating a central authority. It consists of electronic ledgers around a P2P system that enable a community of users to record transactions in a shared ledger each time-stamped and linked to the previous ledger. The name comes from its structure, where each digital record or transaction is called a block, and the transactions linking the electronic ledger together in a single list are called chains (Yaga et al. 2019). The blockchain network contains users and validators. Users interact with the blockchain application and either send or receive transactions (Swan 2015). Additionally, every user in the node holds a copy of the ledger and this feature makes blockchain immutable, tamper-proof, and resistant to hackers and malicious attacks on the system. The aggregator validates the system by approving the transactions occurring in the system and writing those transactions in the block, and appending it to the blockchain.

4.1 Blockchain Architecture

Each block contains data (block version, Merkle tree root hash, timestamp, nBits, and nonce), the block's parent hash, and the previous block's hash, and the data stored in a block is determined by the blockchain network's form. The block version indicates which block validation rules are to be followed while the Merkle tree root hash indicates the value of all the transactions in the block which is then followed by the timestamp. The nBits is then the target threshold of each hash followed by the nonce, a 4-byte field that usually begins at 0 and increases with every hash calculation. Finally, the parent block hash in the blockchain architecture consists of a 256-bit hash value pointing to the previous block (Zheng et al. 2017). Hash, a unique feature that identifies a block and all of its information, is the backbone of the blockchain network. Changes to the block would result in a shift in the hash, ensuring maximum security. The hash of the previous block effectively creates a chain of blocks linking them together and thus creating a blockchain. A peer-to-peer network is used instead of a central network to validate and provide consensus. Each block added to the P2P network needs to be validated by multiple computers to ensure each transaction is valid before it is added to the blockchain (Ante et al. 2021). A digital signature is used to sign each transaction which is verified by the recipient. The typical algorithm used for this is the elliptic curve digital signature algorithm (ECDSA) (Zheng et al. 2017). The integration of multiple computers ensures a single user cannot add invalid blocks to the network making it tamper-resistant. The P2P network ensures the chain is never broken, and each block is recorded.

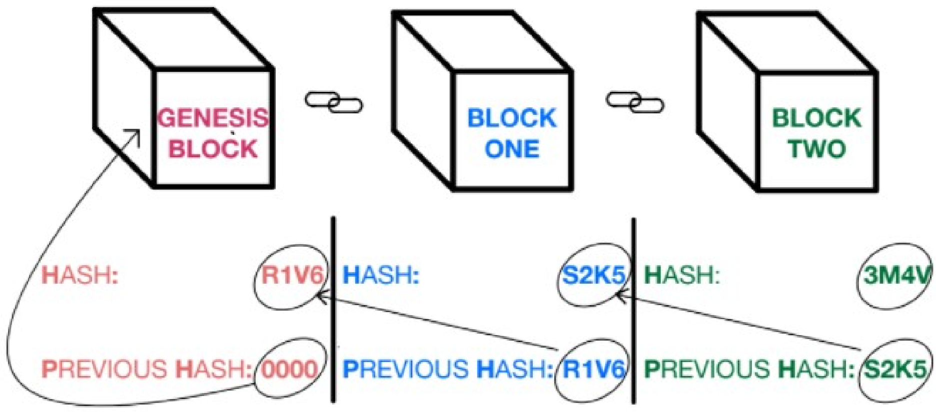

Figure 4.1: Blockchain Structure

4.1.1 Protocol Layer

In blockchains, not all ledgers on distributed nodes are the same. Therefore, protocols are essential to ensure that ledgers in different nodes are consistent. A distributed consensus algorithm allows a system to reach a common decision (consensus), which is recognized by the majority (Gupta and Sadoghi 2019). Blockchain technologies present two common strategies to establish consensus, Proof-of-Work, and Proof-of-Stake.

4.1.1.1 PoW - Proof-of-Work

As stated above, PoW is a consensus strategy. The PoW requires that each node demonstrates an ability to solve the task at hand competing amongst themselves to solve the complex puzzle (Gupta and Sadoghi 2019). The node that has successfully computed the solution will then have the opportunity to generate the next block in the chain. The block is then disseminated to all the other nodes, thus marking the proof that it had successfully done the computation. In this manner, all other nodes have to respect the "winner" and therefore consensus has been reached by continuing to chain on this block (Gupta and Sadoghi 2019). "This type of consensus mechanism relies on proof that enough computational resources have been spent before proposing a value for acceptance by the network" (Bashir 2017).

4.1.1.2 PoS - Proof-of-Stake

PoS on the other hand aims to preserve the decentralized nature of blockchain networks (Gupta and Sadoghi 2019). The PoS algorithm is premised on the idea that the node has enough stake in the system (Bashir 2017). In essence, a node with an n% of resources will receive an n% of time to create the next block. Therefore, the node with higher stakes will lay its claim on the generation of the new block (Gupta and Sadoghi 2019). To determine the stake of a node, a combination of factors is utilized, requiring a set of nodes to act as validators. In this regard, only a validator will be allowed to create a new block. However, to generate the new block, the set of validators will be required to participate in the consensus algorithm (Gupta and Sadoghi 2019). It is important to note that the PoS algorithm consists of two variants; Byzantine Fault Tolerance-style and Chain-based. Chain-based PoS algorithms make use of a pseudo-random algorithm selecting a validator that creates the next block. The most prominent difference between these algorithms, "is the synchronous requirement; chain-based PoS algorithms are inherently synchronous, while Byzantine Fault Tolerance PoS algorithm is partially synchronous" (Gupta and Sadoghi 2019).

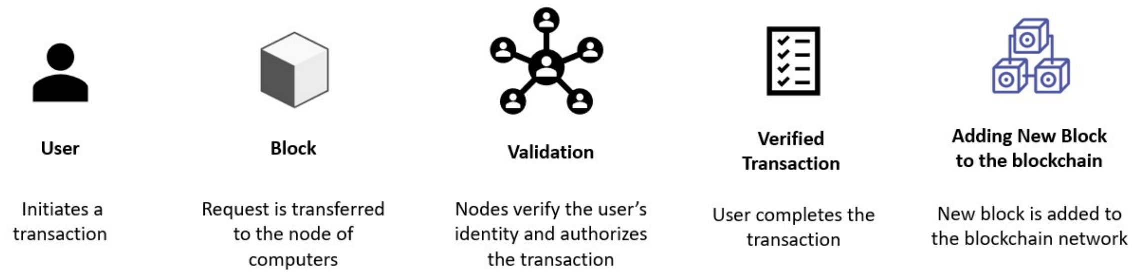

Figure 4.2: Validation of Transactions on Blockchain

4.1.2 Types of blockchain

Many types of blockchains and blockchain applications exist. Blockchain is integrating across platforms and hardware globally in numerous industries (Laurence 2019). Three types of blockchain are most common; public blockchains, permissioned blockchains, and private blockchains. Public blockchains are large distributed networks run through a native token open to anyone to participate at any level with open-source code maintained by their communities. A popular example of this would be Bitcoin (Laurence 2019). Private blockchains are often smaller and do not utilize any token with closely controlled membership. These types of blockchains tend to be favoured by consortiums with trusted members and confidential information (Laurence 2019). Permissioned blockchains on the other hand only allow inter-authorized organizations to construct limited transaction scopes to achieve high transaction performance (Laurence 2019). Permissioned blockchains have recently been characterized with smart contracts - in which business transactions among inter-authorized companies can be executed based on the distributed consensus protocol upon user-defined business logics that have been pre-built with program codes (Sato and Himura 2018). Private blockchain networks will be the basis for our thesis with the EV aggregator considered to be the central authority.

4.2 Benefits of Blockchain

The most attractive and core benefit of blockchain is its decentralization. The consensus mechanism ensures that there is no need for a third party to validate transactions (Bashir 2017). In this regard, a smart contract is developed using blockchain technology to record every transaction between the energy provider and the consumer or between all prosumers in the peer-to-peer energy sharing network. Transparency is another attractive component of blockchain technology. As mentioned before, blockchains are shared and therefore all users on the system can see what has been shared on the blockchain enabling complete trust (Bashir 2017). Trust is one of the core benefits of private blockchains (as used in this thesis) as the disbursement of funds and personal discretion is of the utmost importance. Additionally, all transactions on the blockchain are recorded and cryptographically secured, thus providing integrity and a highly secured transaction network (Asharaf and Adarsh 2017).

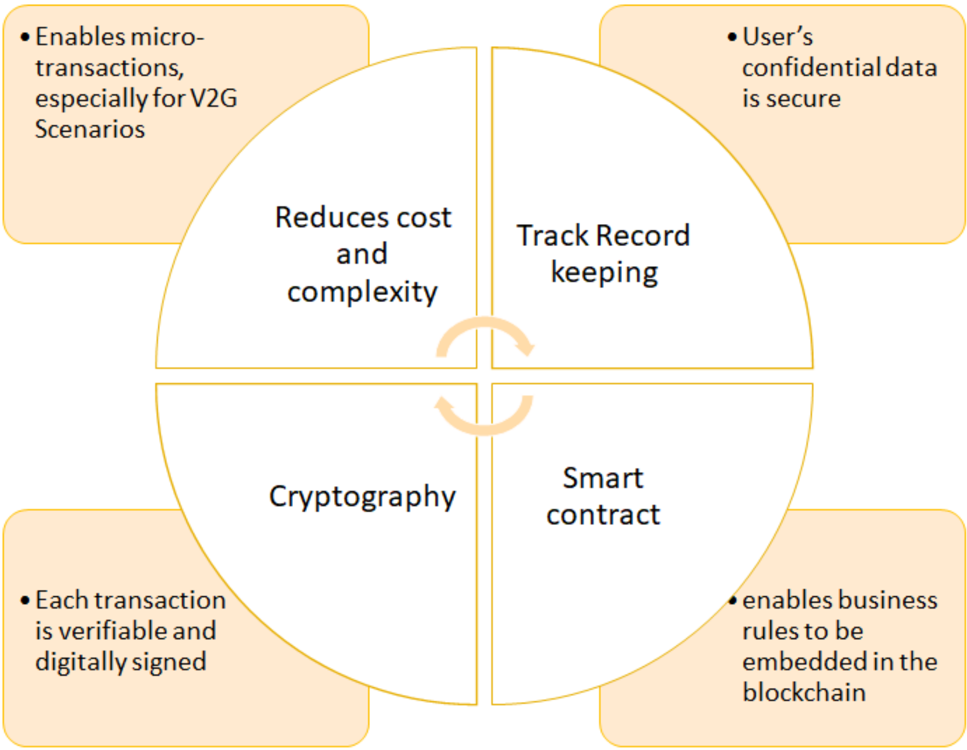

Figure 4.3: Benefits of Blockchain

Once data has been added to the blockchain, it is extremely difficult to change or tamper. Although not completely immutable, due to the level of difficulty in changing the data, an immutable ledger of transactions is maintained (Bashir 2017). Additionally, the system is highly efficient as it is based on thousands of nodes in the peer-to-peer network which is then updated and replicated on each node. In cases where a node may leave the network or become no longer available, the network as a whole will continue to work, effectively making the system run without any downtime (Bashir 2017). Blockchain technology plays a vital role in post-trade settlement functions by enabling faster transactions as it does not require a lengthy clearance and verification process. The agreed-upon data is already available on the shared ledger that can be found between the financial institutions (Bashir 2017). In turn, this fast process eliminates overhead costs in the form of fees paid to third parties. In the example of this thesis, y making use of smart contracts, no third party will have to be paid or any additional fees by the users on the peer-to-peer energy sharing network making it a highly cost-effective network.

4.3 Smart Contract

A contract is a traditional way of enabling a transaction. Though the structural component of a transaction is embedded in the blockchain protocol, constraints suited to each application are specified through a smart contract which was first coined by Nick Szabo in 1994 (Szabo 1994). Smart contracts are autonomously triggered when a certain action is invoked and executed by a consensus mechanism (Luu et al. 2016).

A smart contract is a self-executing and tamper-proof computer program, which contains business logic and control logic of the system (Andoni et al. 2019). It can be triggered automatically and doesn't require third-party verification to authenticate the user requests and interactions. A smart contract contains value, address, state variables, and functions. Bypassing the inputs to the smart contract, and depending on the logic formulation, the appropriate output is returned. All transnational information is available and stored securely Mohanta et al. 2018. Moreover, smart contracts are deterministic and they produce the same outcome for the given input on any number of nodes. Therefore, it is impossible to define a non-deterministic function in a smart contract and execute it in the blockchain. (Christidis and Devetsikiotis 2016). A smart contract can encode any rules in its programming interface which are generally written in object-oriented languages.

4.3.1 Solidity

Solidity is a programming language, designed to write smart contracts and it can be executed by Ethereum Virtual Machine (EVM). It has the conventions of assembly language, web development, and networking. Smart contracts for Ethereum are written in a high-level language. Many languages exist for writing smart contracts namely, LLL, Serpent, Viper, and Solidity. Solidity is a Turing-complete programming language, statically typed, similar to the syntax of JavaScript, supports inheritance, polymorphism, and libraries (Dannen 2017). Contracts in Solidity are similar to classes in an object-oriented programming language (OOPS) and contain functions that modify variables and data which is similar to traditional programming structures. In addition, Solidity contains special variables (msg, block, tx). These variables have special access to the blockchain framework like retrieval of origin address, amount transacted amount and the data sent alongside transaction. Modifiers are other enclosed codes that have the special ability to modify the function's scope and accessibility. They allow the function behaviour to change. They contain a set of conditions that enable the function to be executed or not.

4.4 Ethereum

Ethereum is a public database that stores a permanent record of digital transactions where individuals can make peer-to-peer transactions without the need for a central authority. Ethereum is a blockchain-based virtual machine used in developing decentralized applications (DApps) and smart contracts to define a set of rules and conditions (Wood et al. 2014). The Ethereum blockchain is significantly a transaction-based state machine, it refers to reading a set of inputs, and based on the input the executed transactions transition to a new state (Andoni et al. 2019). Ethereum contains unconventional programming paradigms since the framework is based on blockchain program execution. It provides a distributed platform and a virtual machine called Ethereum Virtual Machine (EVM) that serves as a run-time environment. EVM is a sandbox and fully isolated from outside networks and file-system. This ensures that the smart contract running inside EVM has no access to any outside peripherals. EVM is built on a stack-based language and therefore in hindsight, smart contracts are sequentially executable op-code statements. EVM is a global decentralized computer on which all smart contracts run. It is a pseudo giant computer with smaller discrete individual computers working in harmony. To keep check of the transactions occurring in the EVM, a certain cost is associated with each execution of a code and this is called Gas. Based on the level of computation required for the specific operation, the Gas price varies. A higher computational code cost more Gas and lower computation cost low Gas fees. This structure ensures there is no Denial of Service (DoS) attacks on the system, where a rouge agent tries to bring down the network by overwhelming computations. The other benefit to imposing Gas cost in EVM is to ensure that developers are writing efficient applications without wasting gas on computing redundant calculations (Wohrer and Zdun 2018). Hence, Ethereum is used for a wide spectrum of applications.

4.4.1 Accounts and Transactions

In Ethereum the global shared-state is comprised of many small objects called accounts. There are two essentially two kinds of accounts that hold the same address space. An address space in Ethereum consists of a 160-bit identifier used to classify any account. External accounts are controlled by private-public keys and have no code associated with them. Contract accounts are another type of accounts that are controlled by their contract code and the code is associated with the account. An external account sends digital transactions to other external accounts or other contract accounts by creating and signing a transaction using the private key. While the contract accounts can't initiate transactions on their (Kasireddy 2017).

A transaction is said to have occurred when a message is transmitted from one account to another account. If the transmitted message contains the payload (input), the code in the target account gets executed taking payload as the input. The distinct feature between ethereum and bitcoin is the capability to design and control the interactions between the users that evolves with time. The ethereum protocol is built and designed for decentralized applications, and focusing on short development duration, security, and interactivity (Kasireddy 2017).

4.4.2 Storing data

Ethereum provides three ways to store the data namely, storage, stack, and memory. Every account contains storage that handles the transactions and function calls. An account is a key-value pair that maps 256-bit words to 256-bit words. Memory is secondary data that handle the momentary instances of the function calls. One of the advantages of memory is the ability to access the contents at the byte level, where reads are restricted to 256 bits and writes can be either 8 or 256 bits. Stacks are termed for the computations carried on the data area. EVM is a stack machine and not a register machine (Dannen 2017).

4.4.3 Web3.py

Web3.py is a Python library that fulfils the interaction between the client and the blockchain network. It is commonly used in decentralized apps (dapps) to send transactions, interact with the smart contract, read block data and for a variety of other use cases. Web3 is created for minimal trust environments, especially for shared environments where the participating clients can securely share details among other participants. An important function in the web3 stack is the ability to enable nodes to interact in a decentralized manner. Web3 is a platform-neutral computation language, which means that the interaction between nodes can be encoded at the basic level and ported in various platforms such as ethereum and cryptocurrency. Web3 provides users to interact with the blockchain and execute business logic. With JSON RPC (JavaScript Object Notation Remote Procedure Call) protocol, data is transmitted across each node in the network (Dannen 2017).

4.4.4 Ganache

Ganache is a personal blockchain for rapid development of Ethereum blockchain application and testing the solidity smart contracts. Ganache enables the user to create a private Ethereum blockchain to run tests, execute commands, and inspect the state of the dApps while controlling the blockchain operation. Ganache is inbuilt with 100 accounts for testing purpose. It gives the ability to perform all on the main chain without accounting for costs (Taş and Tanrıöver 2019).

5

Application of Blockchain in P2P Network

The blockchain-based smart grid enables the application of blockchain in the electrical system and looks to future developments in the use of blockchain technology in the energy markets. Rapid development in the power system and IOT devices has resulted in the transition of the energy market designs to control and manage the supply-demand equilibrium of the electricity network. According to the author (Alladi et al. 2019), there are 5 main applications of blockchain in the current smart grid.

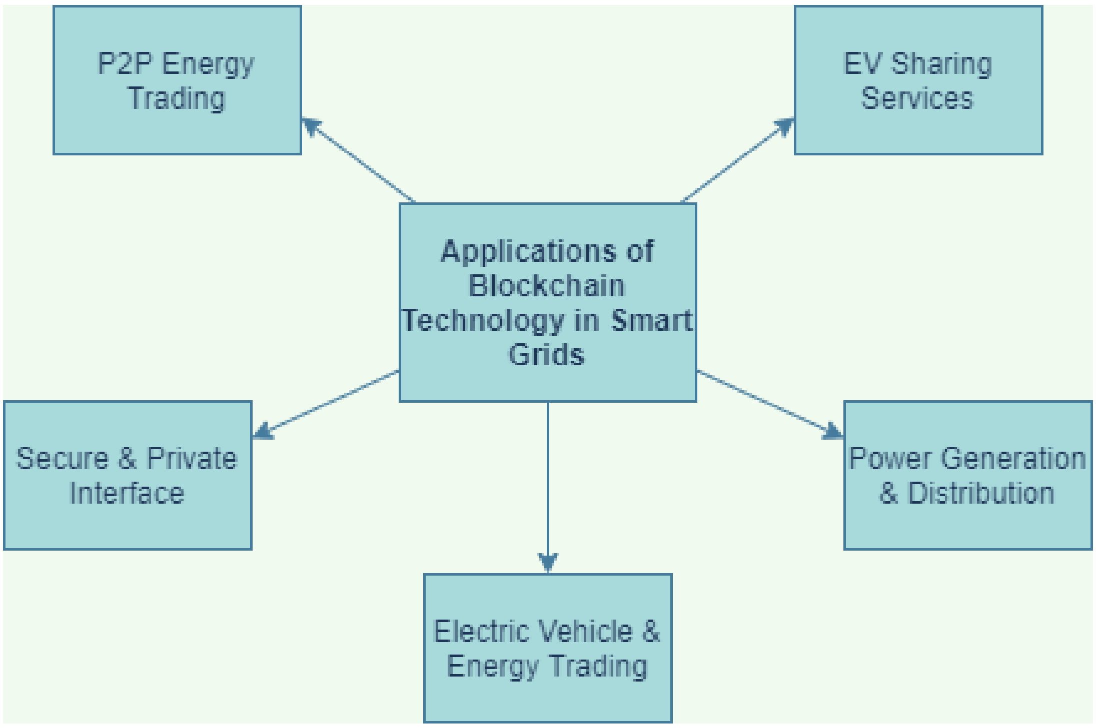

Figure 5.1: Applications of Blockchain in P2P Network

5.1 P2P Energy Trading

Despite the various opportunities and advantages that peer-to-peer decentralized energy trading can bring to the energy system, its full implementation can face many practical challenges (Esmat et al. 2021). With PEVs, we also encounter mobility issues. PEV users are naturally mobile as they do not necessarily charge within their homes which are known as roaming charging (Abdella and Shuaib 2018). Roaming charging can be divided into two categories: Internal Roaming Charging (IRC) and External Roaming Charging (ERC). If the user charges the EV with the same supplier as outside the home it is IRC and if it is a different supplier then it's ERC. Therefore, proper authentication methods and energy flow control mechanisms are needed to allow PEVs' charging or to sell the power by discharging back to the grid (Abdella and Shuaib 2018). A great concern of P2P DET is the impact that discharging has on the EV's battery life. Studies have shown that frequent discharging can cause up to 3 years of battery life degradation (Abdella and Shuaib 2018).

The Peer-to-Peer energy trading model suggested by C. Zhang et al. 2016, encompasses a four-layer architecture that includes a power grid layer, information and communication layer, control layer, and a business layer. This model is based on the Smart Grid Architecture Model (SGAM) which comprises three dimensions. The first dimension addresses the time-dependency of P2P energy trading, where the energy users of the grid send in their bids. After an elapsed time, the bids are settled where a peer (prosumer) is connected to another peer(consumer). The second process is the exchange of energy, where the transfer of power occurs between the agreed two peers. Finally, the third process is a payment where the peers exchange money based on the amount of energy consumed at the agreed price. The second and third dimension describes the size and layers of the P2P network. The blockchain is utilized in the SGAM framework as the Information and Communications layer.

5.2 Electric Vehicle Sharing Services

The main problem in the electric car ecosystem is the charging infrastructure. Also, the EV user has range anxiety combined with the lack of charging infrastructure. Therefore, lack of charging infrastructure as compared to fossil fuel is a crucial aspect among people interested in buying an electric car. With blockchain enabled-charging networks, users can share their private charging infrastructure with others in need. For example, if the private charging network owner does not necessarily use the charging station, the person could make it public so that nearby EV users can utilize the infrastructure. In exchange for the

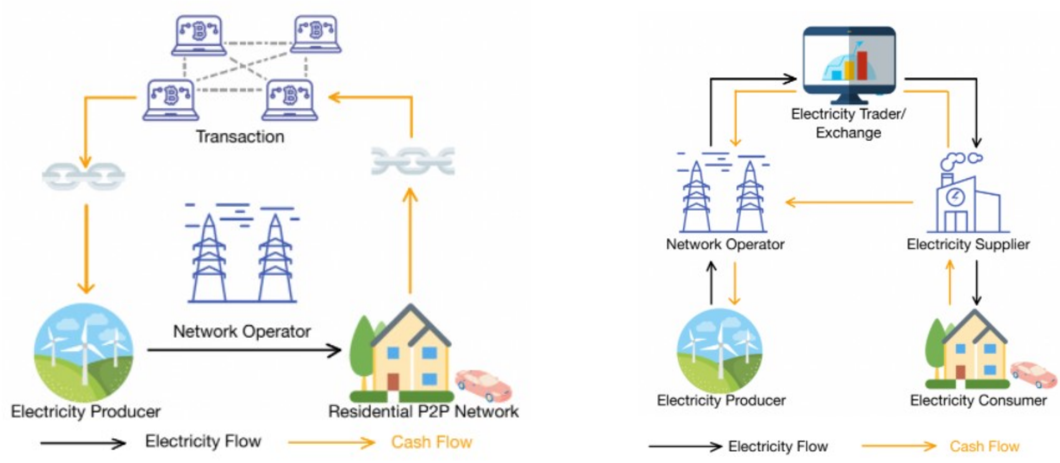

Figure 5.2: Blockchain Approach VS Traditional Approach

services provided to the EV user, the charging station owner can earn some incentives by lending their infrastructure. EV users can locate a free charging station using GPS in the vicinity and engage in charging their vehicle for a small fee provided to the charging station owner. Making the private chargers public opens up a lot of chargers available for EV users. This also results in minimal stress on the investment strategies for building new charging infrastructure.

5.3 Energy Trading and Electric Vehicles

With the integration of electric vehicles to the distribution system operation, the power demand in the energy market increases. The charging of electric vehicles has a sizable impact on the main power grid creating peak load conditions in the demand profile. This charging demand often coincides with the existing load demand, which stresses the local grid and has consequences for adequacy and quality of supply. As a result, the power system can require additional investment in grid and generation capacity units (Ajomand et al. 2020). Electric Vehicles can alternatively be used as a source of electricity (V2G), to power the grid and fulfill the electricity demand of the charging vehicle and thus balance the supply-demand equilibrium. However, in certain cases discharging EV users tend to be reluctant to participate in the electricity trading market and consequently leading to supply-demand imbalance (Alladi et al. 2019). One of the major drawbacks of the current energy system market is the absence of security regarding the transactions due to the involvement of mediators and other third parties (Abdella and Shuaib 2018). A secure electricity trading platform that is decentralized and private is necessary. The blockchain model can be implemented to allow adaptive charging, provide the electric vehicle the ability to charge during reduced electricity-priced hours while balancing the energy trading market. Blockchain technology can also be potentially used to bridge the gap between the prosumer and consumer. The decentralized nature of electric vehicles with multiple actors and complex interactions creates a good basis for the implementation of a blockchain interface.

5.4 Secure and Private Interface

A smart meter is an electronic device used to record information such as electricity consumption, voltage levels, current, and power rating is placed at every charging station in the network. The smart meter ideally records every energy transaction in real-time and in regular short intervals throughout the day (Y. Wang et al. 2018). The energy production and consumption pattern can be accessed by malicious entities disclosing user data and identity. By writing a smart contract on a permissioned blockchain platform the system can be protected against potential threats using multiple independent parties to approve the transaction before considering them valid (Alladi et al. 2019). The stored identity of the user is secured cryptographically and cannot be altered or deleted making the blockchain network a difficult platform for data breach to occur.

5.5 Power Generation & Distribution

Renewable distributed energy resources facilitate emission-free and less expensive sources of electricity. These natural sources such as solar and wind energy will contribute to the current and future energy generation and distribution needs. However, the irregular nature of natural renewable resources and long-distance transmission poses challenges to the energy distribution environment of the system. A smart grid is a modernized power delivery infrastructure that integrates the electricity system in two ways, communication and electricity flow (Ajomand et al. 2020). With the advancement in technology and control methods, the IoT device may provide predictive energy information and corresponding recommendations to alter the energy data such as power usage, production, delivery, and distribution in real-time (J. Liu et al. 2012). Malicious entities could use methods such as Denial of Service (DoS) and Data Injection Attack (DIA) to manipulate and control the user data leading to regional power outages and blackouts (Faquir et al. 2021). Incorporating a blockchain framework into the power generation and distribution system helps prevent data manipulation and theft since one of the key characteristics offered by blockchain is data immutability (Alladi et al. 2019).

6

Methodology

A method defines the path of achieving the goals set forth by the researcher, which often requires a culmination of methodologies to formulate and understand the problem (Easterbrook et al. 2008). To encompass the complex nature of implementing a blockchain framework for EV charging networks, a quantitative research approach is used. Quantitative research deals with the measurement of amount or quantity. Within the Quantitative research method, the simulation approach is a sub-division that deals with the creation of an artificial environment with self-generated data (Kothari 2004). A particular research approach is employed to study the dynamic behavior of the modeled system. But addressing a complex problem requires multiple research methods to define and develop the scope of the thesis (Andrew, Halcomb, et al. 2009). Exploratory types of research are used where the problem statement is relatively new, while descriptive and evaluative approaches are used with more mature problems. Though blockchain as a technology is relatively new, the problems which are addressed to solve are mature. Alternate methods and approaches to solve the growth of EV and the charging infrastructure using blockchain are evaluated and discussed extensively in the literature review.

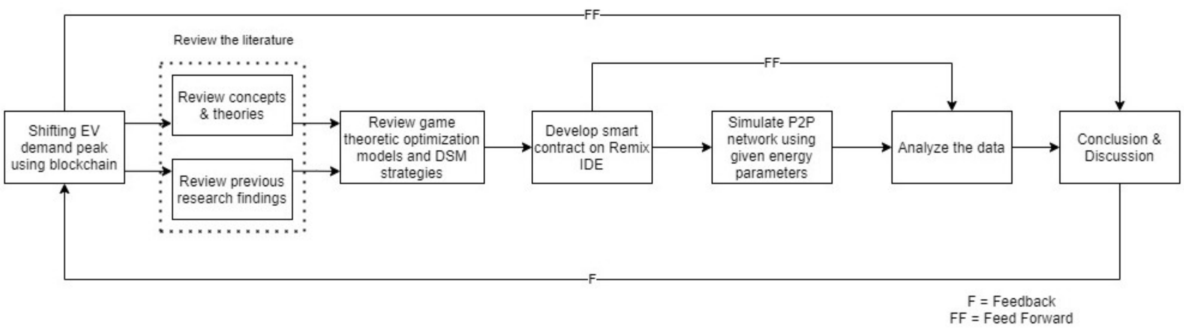

Figure 6.1: Research process flow chart adapted from Kothari 2004

The chart describes the activities proposed to be performed as iterative and overlapping for specific tasks despite being sequential at first. The problem statement is formulated with a thorough understanding and research of the literature. The conceptual and empirical literature is analyzed extensively to narrow the scope of the research question.

6.1 Literature Review

Uncontrolled EV charging puts the grid at risk of failure due to overloading, the implementation of a blockchain-enabled energy sharing network eliminates network congestion (Lazaroiu et al. 2020).
Million's of EVs can be exploited for bidirectional charging and peer-to-peer energy trading. Best practices guidelines for Peer-to-peer EV charging services are devised by Matzner et al. 2018, and also laid down necessary processes to provide for the user. Considering EV user preference into scheduling process increases collective revenue from EV aggregators (A. Al-Obaidi et al. 2021). A dynamic pricing framework for peer-to-peer energy between charging utility and business edifice with solar generation reduced the operational expenses and increased the PV consumption for prosumers (Aznavi et al. 2020).

Taljegard et al. 2019 carried out V2G implementation in 4 different regions in Europe and concluded various benefits to the energy system, which includes (i) reduce investments in peak power capacity in all the regions investigated; (ii) reduce the need for short-term and long-term storage technologies other than EV batteries (i.e. stationary batteries and hydrogen storage); and (iii) stimulate increased shares of solar and wind power generation, as compared to direct charging in some regions (mainly Hungary).

Blockchain-enabled energy technologies provide a transparent, tamper-proof, and non-intermediary eco-system that benefits system operators, customers, and the whole energy system. Moreover, blockchain has a prominent role in promoting the distributed generation and monetizing small-scale generators (Andoni et al. 2019). Novel energy market structures are also developed using blockchain framework for big-industrial energy users according to contract Dang et al. 2019.

Charging utility operation can be maximized by optimal scheduling of the EV charging through a permissioned blockchain network to overcome potential security and risks associated with existing opaque energy markets (Asfia et al. 2019). Having a smart contract to enable EV user participation in peer-to-peer energy sharing results in increased profits for the EV user (A. A. Al-Obaidi and Farag 2020).

Distributed ledger technology (DLT) enables grid operators to leverage EVs which aren't in use to provide ancillary services and to balance the grid (Garrido et al. 2020). With a tangle light-weight data structure and game-theory model, DLT for the V2G network can cost-effectively enable micro-transactions without requiring intense computational power (Hassija et al. 2020).

Y. Li and Hu 2019 introduced the concept of zonal scheduling of EV charging using blockchain framework to reduce the overall load variance of the distribution network under the constraints of power flow. Pustišek et al. 2016 modeled an ethereum blockchain network for locating the cost-effective nearest charging station for an EV. Pajic et al. 2018 formulated a scheduling system to solve the valley filling problem by introducing slot-based booking for EV charging to reduce under-utilization of grid resources. Z. Li et al. 2020 proposed energy storage to manage the additional power with blockchain as the underlying architecture to reduce the complexity of P2P transactions. Pop et al. 2018 framed ethereum based demand-side programs in smart grids using Proof-of-Stake methods. The author re-frames the centralized system into distributed consensus network to cater the growing EV demand.

Leveraging decentralized ledger technology, C. Liu et al. 2018 maximized trading efficiency by controlling the charging rate to control the charging and discharging process. V2G energy trading with smart contract in Ethereum designed by H. Liu et al. 2019 proved effective than the traditional power trading system. Madhu et al. 2019 formulated a large-scale solar PV-powered community grid-enabled EV charging station, with an underlying layer of blockchain to hold the account of each owner. With blockchain as a service, Vehicle-to-Vehicle (V2V) and Grid-to-Vehicle (G2V) can be performed in a peer-to-peer (P2P) manner in absence of a central entity (Javed et al. 2020).

By surveying the literature, the research gaps were predominant in defining the working architecture of the blockchain with the inclusion of EV charging in the P2P energy network. While the authors try to define the State-of-Charge of the vehicle to compute the state of the system, depth of discharge is missing to be considered in the calculations. One of the crucial factors in determining the battery's State-of-Health is the depth of discharge of the battery, which should be taken into consideration if V2G charging is included in the system.

Depth-of-Discharge (DoD) is an important factor in influencing the battery's life cycle (C. Zhou et al. 2011). The feasibility of V2G charging is influenced by the degradation cost of the battery as it directly affects the cost of the system from a lifetime perspective.

Degradation of the battery also depends on the battery chemistry, the two most used battery compositions are NCA (Lithium Nickel Cobalt Aluminum-oxide battery) and LFP (Lithium Iron Phosphate battery). Two main parameters used to define the degradation aspect are Depth of Discharge and Life-Cycle Performance, where the depth of discharge is mainly seen in NCA while life cycle performance, a linear function is seen in LFP.

Farzin et al. 2016 established a practical wear cost equation for the degradation of the battery in EV due to vehicle-to-grid applications. C. Zhou et al. 2011 assertion on the link between the battery degradation and the type of charging optimization is reflected by Farzin et al. 2016 as well.

He et al. 2012 describes the major hindrance to the scheduling problem, which is defining the global and local optimal system for EV charging and scheduling. The author defines that the global system deals with the prediction of future use and routines of EV users, whereas the local system optimizes the given subset of EVs at the charging stations in real-time. However, defining the global system is difficult because the future choices of the EV users should be predicted and the stochastic process of EV scheduling and charging can be quite challenging. Local optimal charge scheduling, on the other hand, can achieve maximum optimization of the system because it can deal with the dynamic system changes and scales globally according to the current number of vehicles connected to the charging station.

Crow et al. 2016 addressed the grid congestion problem due to the proliferation of EVs using static and dynamic frameworks and the results showed that the global optimal EV charging mechanisms are not optimal due to the stochastic nature of the EV user behavior. EV aggregators are considered in the proposed distributed ledger system because the purpose of the aggregator is to forecast day-ahead EV loads and make bids to TSO. This is essential to settle the electricity demand and many uncontrollable variables in EV charging.

Therefore, the research is focused on modelling the charging infrastructure of a P2P network with the assumption that the building has renewable energy generation, i.e., solar energy. The electric vehicle's battery state is used as the input parameter to initiate the charging request to the charging station. Depending on the best possible scenario for both the parties (EV and utility grid), the electric vehicle charges at cheaper time slots and shifts the EV load dynamically to reduce/shift the demand peaks.

With the optimization formulation in place, the smart contract is written with solidity, a Turing language, that holds the functions and the clause that is triggered when specific criteria is met. Python script acts as an intermediary, that contains the script of the parameters of the real-time vehicle data with the specific energy parameters. With those parameters, functions in the smart contract are called to maximize the profit for both the players, in turn minimizing the operational costs.

The research study is to propose the blockchain as a service by implementing a game theoretic framework involving interaction between an electric vehicle and a charging station, which happens to be connected with the building energy system and the distributed energy system. (Jin et al. 2013)

6.1.1 Assumption

- A residential energy network is considered as a working model for this thesis.
- The range needed for an average electric vehicle to travel the next day is considered to be 200km considering the total range of an EV is 400kms. We model the charging infrastructure in a way that the SOC of the battery during V2G charging does not drop below 50
- In our model we assume the SOC of the battery to be 100 per cent during the V2G charging condition. But to reduce the degradation of the battery the user could choose to discharge from 70 to 40 per cent.

6.2 Model Formulation

Figure 6.1 is used to develop the system boundary and optimization model. Defining the problem is crucial before defining the limitations of the model. The model is simulated by defining the system boundary and the constraints. The model aims to solve the EV charging infrastructure in the P2P network and attempt to shift the EV charging from the grid during peak demand hours. By formulating a control mechanism to charge the EV with the peers in the system, the cost of EV charging is reduced and revenue for the peer selling the energy is maximized. To solve the peak demand problem from a grid perspective, a game-theoretic model is introduced to influence the user behavior in affinity to move away from the peak demand region.

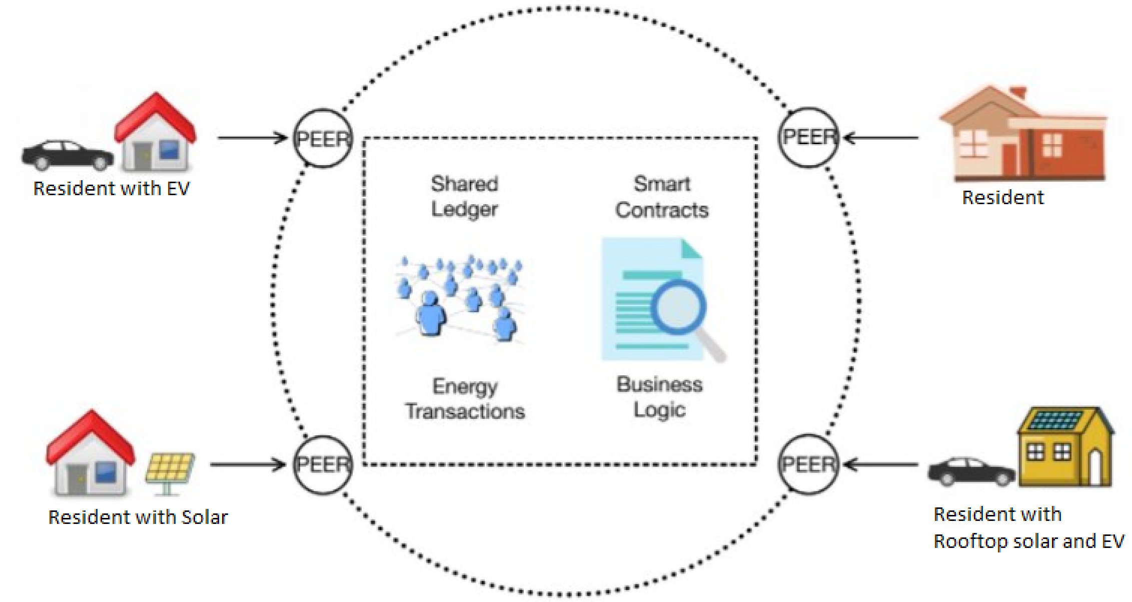

Figure 6.2: P2P Blockchain Network

6.2.1 Smart Grid and Logic Structure

The proposed P2P system is formulated through a programming logic structure. The logic structure takes three inputs from the EV user as the input parameters to begin the charging process, namely, battery capacity, battery initial capacity and the user-specific end time. Battery capacity refers to the maximum capacity of the EVs battery, battery initial capacity refers to the SOC of the battery when the EV connects to the charging station and finally, the user-specific end time is the time duration given by the user to disconnect the electric vehicle from the charging station.

After EV has parsed the three parameters to the blockchain network, the required energy in KWh (B_{chg}, time for EV to charge (δ t), and the real-time state of the battery (Q) is calculated. Firstly, the model checks whether the nearest PV source satisfies the energy demand of the household and is willing to trade energy to the grid. A further decision is made whether the PV production can satisfy the EV demand, else the PV production only satisfies a part of the EV demand. The EV charging moves on to V2G charging by checking if the nearby idle EV could satisfy the EV demand. In this scenario, if the demand is not met by V2G charging capability, the grid would provide the necessary energy demand to satisfy the charging demand. When it chooses to charge with the grid the user-specific end time and the computed δ t, real-time prices of the electricity for the user-specific time slots are sorted in ascending order to find the cheapest hours for the EV to schedule the charging.

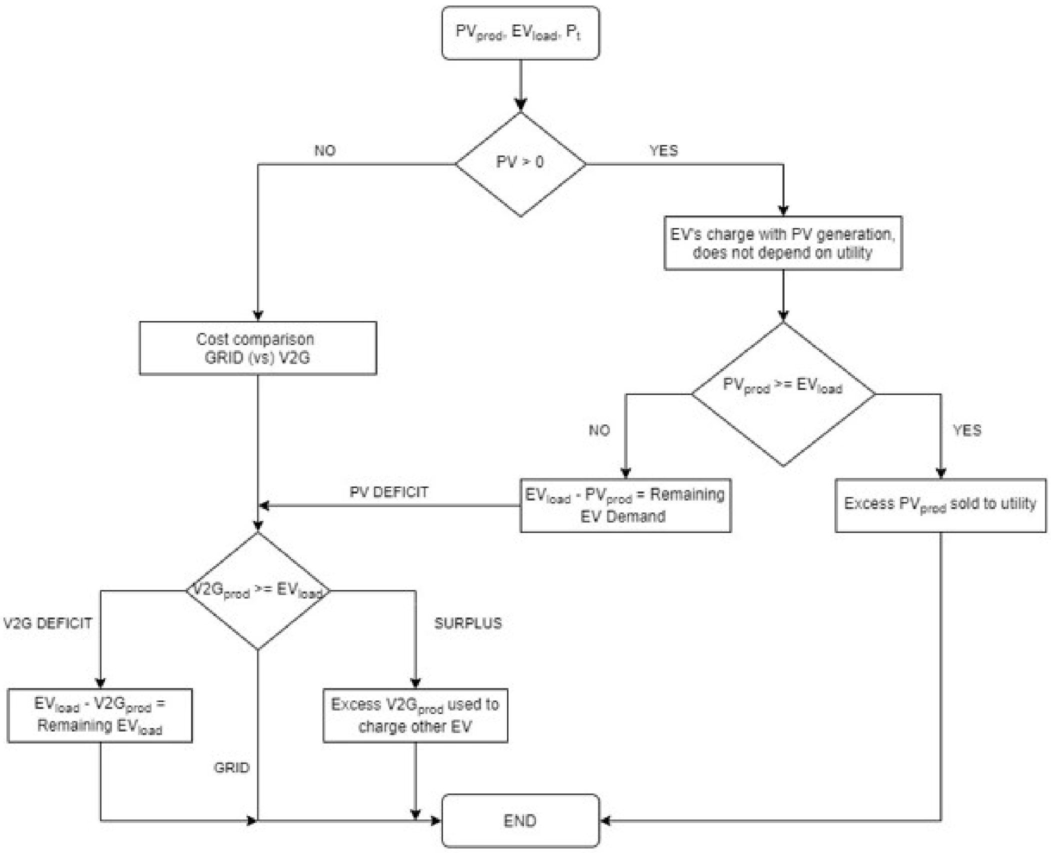

Figure 6.3: Concept Network diagram

6.2.2 Prosumer and EV user

EV user schedules the electric vehicle charging to minimize the energy demand of the local grid. If the prosumer produces a lot of solar energy resulting in overproduction, the excess energy is sold to the grid or EV user who is willing to purchase the surplus electricity. Moreover, in the P2P system, the prosumer has to compete with other bidders to sell their excess energy to the EV users.

The grid utility sets an electricity price λ for each hour t and a Feed-in-Tariff price γ. The Feed-in-Tariff price is the electricity price set by the utility for the prosumers to sell their surplus green energy production at a supply-demand equilibrium price.

Prosumer ensures their profitability by considering the actual electricity Feed-in-Tariff price set by the utility. Therefore, λ has a causal effect on the price prosumers set to sell their energy to EV users, making prosumers to set their price less than λ so that from EV user's perspective, it is economical to purchase it from the prosumer rather than the grid. Since each prosumer acts to maximize their own profit, bids for the selling price differs among prosumers. If the prosumer bid does not get accepted by the EV user, the bid can be sold to the grid at feed-in tariff price.

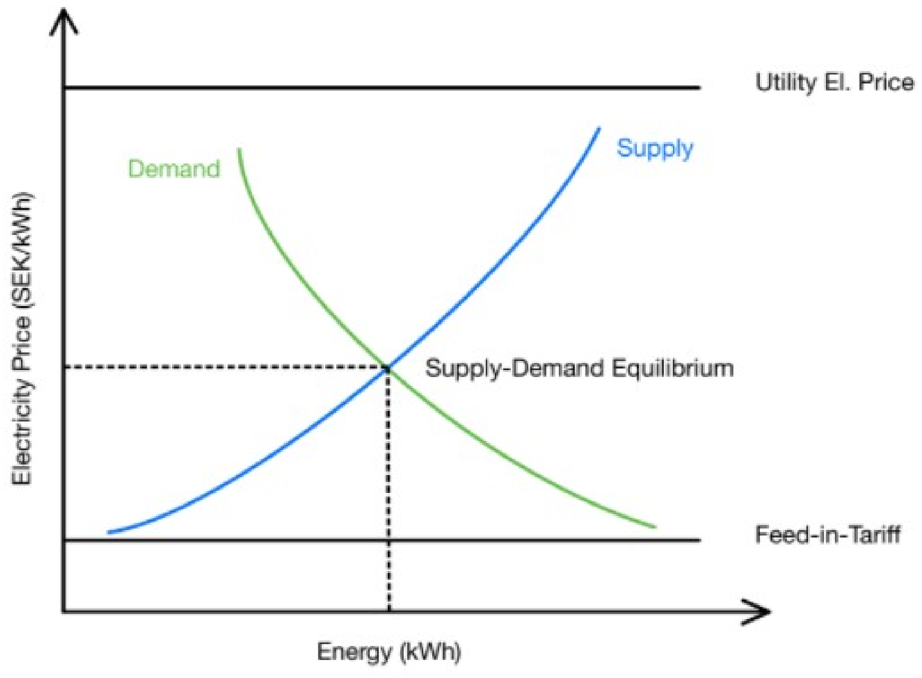

Figure 6.4: Equilibrium supply-demand curve

For this model, EV aggregator gets the demand bids and supply bids from all the EV users and prosumers in the smart grid within a specific location. EV aggregator sets the supply-demand equilibrium price for prosumers to sell the electricity within that specific range under consideration. An assumption is made to compute the price dynamically according to the number of prosumers and consumers connected to the smart-grid at a give time period. So, for each time slot t, the EV aggregator sets a defined supply-demand equilibrium price to facilitate the transaction between both the consumer and prosumer.

After the price has been set by the EV aggregator for the given time slot, EV's try to connect to the prosumer according to two conditions. Firstly, EV checks if the PV in the system can satisfy the demand. If the criteria is met, then the EV sorts the potential PVs according to the nearest distance from the vehicle and establishes a connection.

6.3 Game Theory

Interaction between the EV user and the grid is modelled according to non-cooperative game theory.

6.3.1 System Model

In the following game, the grid is modelled as a player, and N-EV users, each with unique battery capacity, driving patterns and battery degradation parameters. The agents in the game are assumed to be hyper-rational and the day ahead electricity prices for each slot is already known. The time scale of the given model is 24 hours, represented as T=24 time slots in a day. Let N be the EV users and T be the time slots and to ensure cardinality, N= { 1, 2, .., n, ..N}, T= { 1, 2, .., t, ..T} where N $\triangleq |N|$, T $\triangleq |T|$, n $\in$ N, t $\in$ T.

Let the consumption pattern of the EV be X, where X= { 1, 2, .., x, ..X} and x $\in$ X.

Let Battery initial capacity be B_{init} and the battery capacity of the EV be B_{Cap}.

The charging and discharging power of the EV is set to be constant and denoted as B_{pr} and B_{dsg}

The battery does not ideally charge at the desired rated power because there is a loss in efficiency in the transfer of power from and to the batteries. Both charging and discharging efficiency is assumed to be 0.95. η_{chg}=0.95, η_{dsg}=0.95.

Energy stored in the battery during the charging and discharging event of the vehicle is given by B_{chg} and B_{dsg}.

$$B_{chg} = B_{pr} * \eta_{chg} * \delta t \tag{6.1}$$

To avoid simultaneous charging and discharging of the electric vehicle battery, a condition is formulated to allow unidirectional flow of power at a given point of time.

Total energy in the battery at that point in time is defined by:

$$Q_i^t = B_{init} - (B_{dsg} - B_{chg}) \tag{6.2}$$

The total energy in the battery is limited by the maximum capacity of the battery denoted by B_{cap}.

In this model, EV aggregator acts as the energy provider and predicts the EV demand for the day-ahead according to the historical EV demand data and sets the electricity price for each time slot. Cost based pricing model suggested by Nguyen et al. 2012 describes a distributed algorithm where each player in the system individually adapt to the price changes and always chooses the cheapest prices to charge the EV.

Pricing Model:

$$\lambda_t = \phi_t + \sigma_t \tag{6.3}$$

λ is the price signal that depends on the summation of all the EV demand for each time slot.

ϕ is the base price of the electricity that is set by the EV aggregator based on the forecasted EV demand for each hour the following day.

σ is dynamic and changes according to the EV demand present in the next time slot.

$$\sigma_t = \mu(q_t - Q_{forecasted}) \tag{6.4}$$

q_t is the summation of all the EV demand at time slot t, $Q_{forecasted}$ EV demand for the each time slot, and μ is the correction factor. If $Q_{forecasted}$ value is greater than q$-t$, σ becomes negative and brings down the value of λ. This means if the EV demand at a particular time slot is less than the forecasted amount, price of the electricity at that time slot reduces and thus encourages more users to charge their vehicle at this time slot. On the other hand, if the q_t is greater than the predicted EV demand $Q_{forecasted}$, λ increases and pushes more users to shift their demand to another time slot. The above equation influence the charging pattern of EV by dynamically changing the electricity price according to the EV demand. Using the above dynamic pricing algorithm, energy demand is spread equally over entire time slot.

6.3.2 Utility Function

Utility function is the net gains from each users strategies to a given price at given time slot. The dynamic price λ not only depends on its own energy consumption but all the other EV's as well.

$$U_i((\boldsymbol{x}_i, \boldsymbol{a}_i \mid \boldsymbol{\lambda}), x_{-i}, a_{-i}) = -\sum_{t=1}^{T} \lambda_t \left(x_i^t + a_i^t B_{cap_i} \right) \tag{6.5}$$

x$_{-i}$,a$_{-i}$ shows the strategies adopted by other EV user, except the user i. EV users do not interact with each other, every EV user aims to maximize one's own profit. Since EV's does not cooperate among themselves, non-cooperative game theory is employed to model the user's best response of charge scheduling.

6.3.3 Non-Cooperative Game Theory

In a P2P decentralised energy trading market, an EV user always aims to maximize the utility function, without conforming with other player and always chooses according to their best interests, by minimizing the total cost of EV charging by choosing the cheapest hours to charge the vehicle. Therefore, non-cooperative game theory is used for formulating game theory optimization. In this non cooperative game model [N,x$_i$,a$_i$, U$_i$], N = 1,2 ... N is the set of EV users, x$_i$,a$_i$ is the best strategy and U is the utility function for user i. Based on the non-cooperative game theory, each EV user acts independently and chooses a strategy to maximize the payoff function.

$$\{\boldsymbol{x}_i, \boldsymbol{a}_i\}^{\text{best}} = \underset{\boldsymbol{x}_i, \boldsymbol{a}_i \in \mathcal{F}_i}{\arg\max} U_i \tag{6.6}$$

The solution of the game is Nash equilibrium, where the strategy s* played by a user i is the maximum payoff an user i can receive, and no other strategies played by other people can possibly achieve more profits, assuming that every other strategy by users follows the strategy other than user i denoted by x$^*{}_{-}i$.

Nash equilibrium for a non-cooperative game model is a strategy profile x$_i^*$,a$_i^*$

$$U_i\left(\{x_i^*, a_i^*\}, \left\{x_{-i}^*, \boldsymbol{a}_{-i}^*\right\}\right) \geq U_i\left(\{\boldsymbol{x}_i, \boldsymbol{a}_i\}, \left\{\boldsymbol{x}_{-i}^*, \boldsymbol{a}_{-i}^*\right\}\right) \tag{6.7}$$

6.4 Smart Contract Methodology

Github repository link: https://github.com/raghuvar-vijay/MasterThesis_EVCharging

With the problem statement and optimization problem statement formulated in the previous section, the smart contract is developed methodically in the following manner.

1. Develop class diagram to visualise the code structure
2. Define the visibility for the state variables and functions
3. Specify access modifiers for variables
4. Define validations for input variables of the functions
5. Define the conditions that must hold true
6. Express the conditions which were formulated in the model definition decoratively.

The application's proof of concept is visualised through smart contracts which are developed using solidity in Remix IDE and python script. The game theory optimization in the above section is realised by deploying the above smart contract in the ethereum virtual machine. Smart contracts are forked into four domains. EV user authorization, EV scheduling, charging control, and billing.

Python script resembles an EV and for simulation purposes, 4 python scripts are formulated. Owner script resembles the EV aggregator who has specialised access to the smart contract. Owner script is the only entity that can access special functions to add new members and de-register them as well. Only the owner contract can access all the EV's connected to the system in real-time. The other 3 python scripts refer to the individual EV's that interact with the blockchain environment.

Ganache contains the randomly generated addresses for the EV users. These addresses are assigned to each of the EV's python script and this is the key to access the EV charging service in the ethereum blockchain. Though localhost, the python script interacts with the local server port. Also, it is the same port through which the individual EV python scripts interact with the Web3 portal

6.4.1 EV User Authorization

Authorization smart contract can only be accessed by the EV aggregator or the DSO who are deploying the contract. Only the authorised users who are already registered in the system can access the charging services. Moreover, only the authorizer, which is the EV aggregator, in this case, can add new users into the system which makes it more secure and malicious activities.

User on-boarding process: Both EV user and prosumers make a request to the system with their unique 20-bit address with their wallet connected to the

6.4.2 EV Scheduling

EV scheduling is the next part of the smart contract that contains the logic structure of when the EV will be charged in the preceding order of preference. First with the PV, then V2G and finally with the grid.

When the PV is connected with the charging station the location of the PV is also received from the user in the form of GPS coordinates. Firstly, EV checks for nearby prosumer who are willing to participate in local energy trading with the EV. The prosumer then sends in production bid, the price for the bid is less than the electricity price at that hour but more than the feed-in tariff set by the EV aggregator. For the purposes of the simulation, the price is decided to be the average between the feed-in tariff and the grid.

From the EV's prespective, as soon the EV is connected to the charging station, the vehicle looks for nearby PV peer to charge the vehicle. The EV connects to the nearby prosumer based on the GPS coordinates and only if the demand can be met by the solar production.

For the EV to charge from the grid, the EV charging schedule is optimized to choose the minimum price hours within the user-specified end time. Before the EV requests the grid to charge, the wallet balance of the user is checked to know whether the user has enough tokens to carry out the charging. According to the non-cooperative game model, the interaction between the EV user and EV aggregator is programmed as an algorithm in solidity. Initially, the EV sorts the cheapest hours off-chain and invokes in the blockchain interface. Similarly, many EV's in the system connects and schedules its charging according to the cheapest hours. The EV aggregator gets the overall data of EV charging scheduling and computes the dynamic prices (λ) for each slot according to the cumulative demand of all the EV's in each time slot. EV is charged according to the scheduled hours and finally when the charging is complete, the changed price due to dynamic pricing is computed and the transaction is settled between the EV aggregator and the user.

6.4.3 Billing

According to EV's scheduled charging time slots, the corresponding price of charging is recorded to the user data. Each user is pre-loaded with enough tokens to facilitate the transaction for using the charging services. EV user transfers the token to whichever entity the EV user consumers the electricity to charge the vehicle.

7

Simulation and Analysis

The following peers are modelled for the simulation. Two EV users (EV1, EV2), three prosumers (PV1, PV2, PV3), and a grid utility (EV aggregator).

7.1 User Registration

The first step of the model involves the registration of the EV user and the PV user to the blockchain interface. Each user is assumed to have a wallet and an unique address. The unique 20 bit hexa-decimal address is used to map individual users inside the blockchain. The smart grid consists of following peers for the simulation process, two EV users (EV1, EV2), three prosumers (PV1, PV2, PV3), and a grid utility controlled by the EV aggregator. Upon registration a unique ID will be created for the user linking him to the blockchain network.

7.2 Getting input parameters from EV and PV

To validate the blockchain infrastructure the smart contracts are deployed on Remix IDE. The simulation is tested on a private local blockchain test network using Ethereum, namely Ganache without using actual costs while recording transactions. The simulations are performed with specifying the following input energy parameters for the electric vehicle:

Table 7.1: Current energy state of the electric vehicles

Parameter	**EV1**	**EV2**
Battery Capacity (kWh)	100	100
Battery Initial Capacity (kWh)	58	90
State-of-Health	88	88
User Specific End Time (hours)	5	10
Location	57.697437, 11.984428	57.689747, 11.978311

Table 7.2: Energy parameters of PV

Parameter	**PV1**	**PV2**	**PV3**
PV Production (kWh)	30	40	45
Location	57.6984, 11.9859	57.6998, 11.9840	57.6978, 11.9840

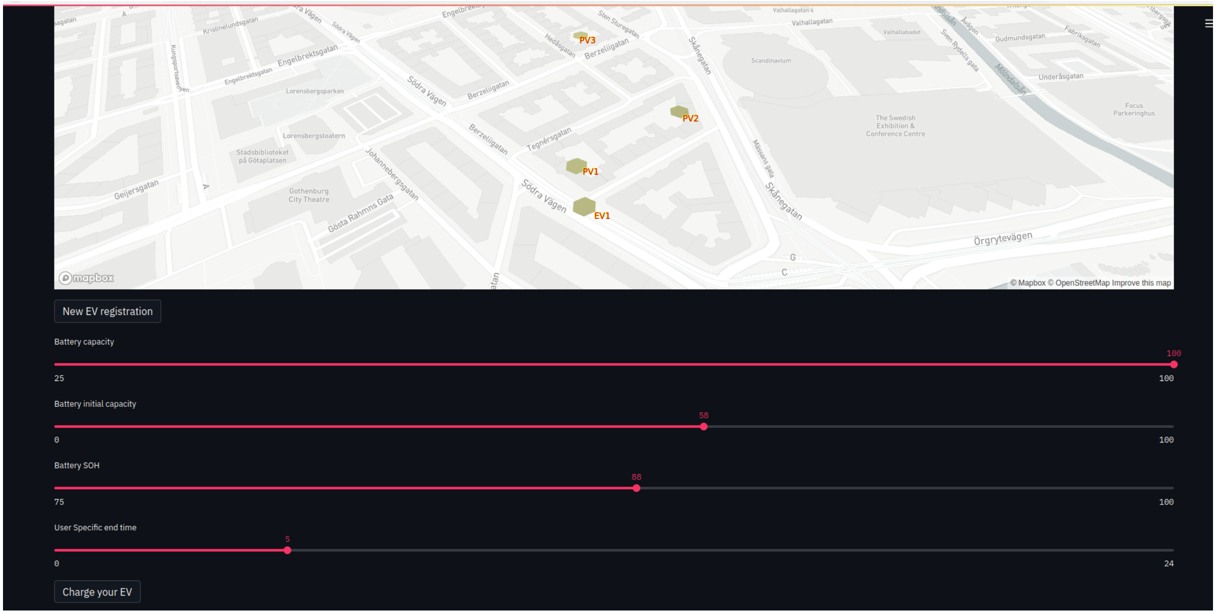

Figure 7.1: Excerpt from the front-end app

Fig 7.1 represents a front-end app depicting how the interface would appear for the EV user to interact with the blockchain. This can be assumed to be the interface of the charging app at the EV user's end. The four EV parameters shown in the figure 7.1 are the input parameters to initiate the EV charging.

The charging process is broken down into three scenarios and a proof of concept is performed by implementing those three scenarios on the Ethereum platform to perform efficiency and feasibility of the blockchain infrastructure.

7.3 Scenario 1: EV charging by PV

In this scenario, EV1 is connected to the charging network, where it checks whether the nearby PV production unit is able to satisfy the EV1 demand. The model consists of three PV generation units nearby as shown in fig 7.1, with surplus production of solar power that would provide flexibility to the electricity system.

Assumptions for scenario 1:

- EV1 connects to nearby PV only if it can satisfy the entire EV demand.
- PV production is forecasted and will produce exactly the predicted amount of energy.

PV1 is assumed to have a production profile starting from 9 AM to 6 PM as shown in fig 7.2 in blue curve. EV1 connects to the charging port at 10 AM. EV1 computes the required energy level of the battery and a tentative user end time of when the user is going to drive the vehicle again within the smart contract. The smart contract computes required amount of charging for EV1 and this is termed as demand bid form the EV1. EV1 then checks whether nearby PV could satisfy the demand. The nearby PV's posts the supply bid in terms of available energy and a corresponding price. According to fig 6.4, the supply-demand equilibrium price is set for one time slot for all the peer interactions taking place in that region. If the PV satisfies EV1 requirements are satisfied, EV1 is connected with the corresponding PV. In this case it is PV1, because it can satisfy the EV1 demand and it is the closest to the car. The unsettled PV production bids PV2 and PV3 are settled with the grid at the feed-in-tariff.

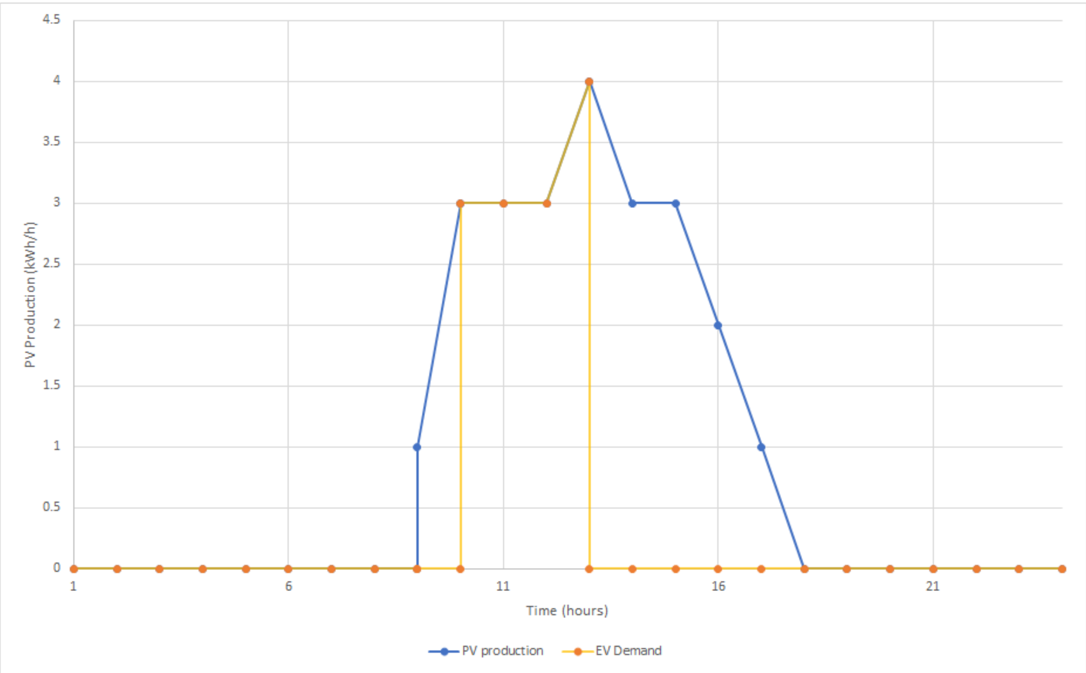

Figure 7.2: Electric Vehicle charging from the solar

Figure 7.2 depicts the charging pattern of EV using PV. X-axis represents time in hours and y axis represents production/demand in kWh/h. The blue curve represents the PV1 production profile and the orange curve represents EV1 charging profile. From 10 AM to 1 PM, PV1 is producing excess solar power and wishes to sell the energy to nearby peers.

7.4 Scenario 2: EV charging by V2G

If the nearby PV cannot satisfy the EV1 demand, the EV1 looks for nearby EV with V2G capability to charge the vehicle.

Assumption for scenario 2:

- All vehicles in the model is assumed to have NCA battery chemistry.
- For NCA battery, discharging the battery at 1C does not affect the battery life of the vehicle.
- For maximum battery life cycle retention for and to diminish the calendar ageing of NCA batteries, only vehicles with SOH higher than 80 is considered for V2G.
- Also, the vehicle is only allowed to discharge up to 50% SOC of the vehicle, since for NCA battery chemistry, DOD (Depth of Discharge) affects the battery life.

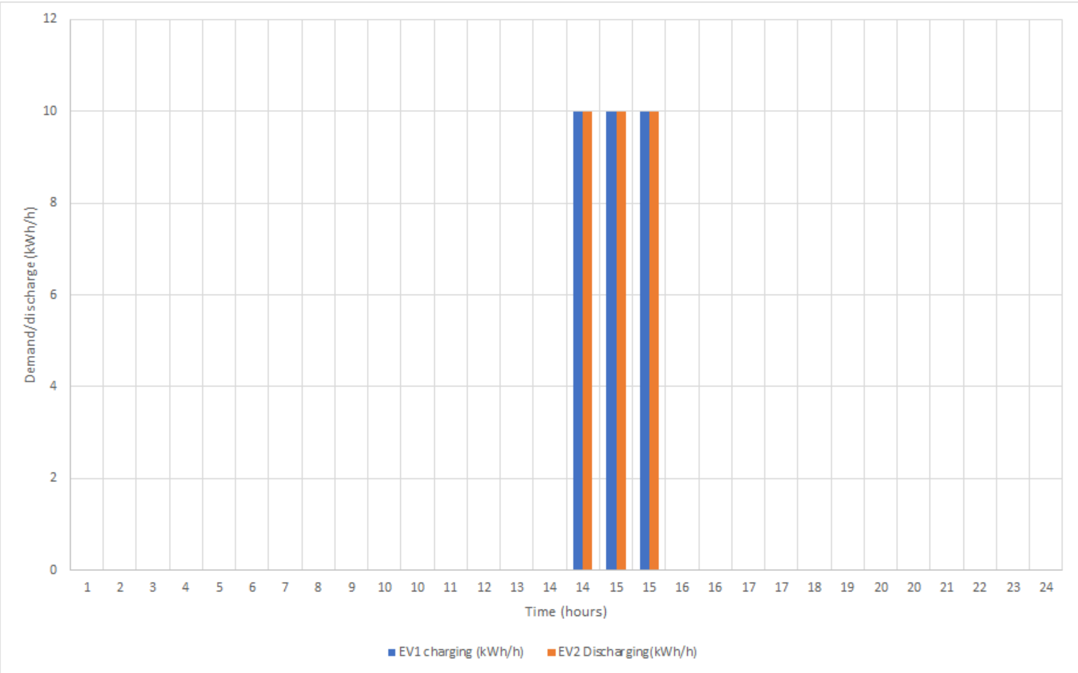

Figure 7.3: Electric Vehicle charging from nearby v2g

Similar to scenario 1, EV1 checks the energy parameters of the nearby EV's providing the V2G services and connects if it can satisfy the EV1's demand. In this scenario, EV1 chooses EV2 because it satisfies the demand and is closest to the location of EV1.

From the figure 7.3, EV2 discharges 10 kWh/h energy and EV1 consumes the exact amount at each time slot. At the end of charging

7.5 Scenario 3: EV charging from grid

Assumptions:

- Dynamic charging of EV at cheap priced electricity hours
- EV is assumed to be connected for a longer period to show the peak demand shift

If EV1 does not find the necessary battery energy demand to charge from nearby PV or V2G, the demand is satisfied with electricity provided by the grid. The EV aggregator sets the price of electricity for the day ahead for each time slot based on the forecasted EV charging demand from the historic time series data. EV1 chooses the cheapest hours of electricity to charge the vehicle that is within the user's end time. Finally, the scheduled charging based on the game theoretic optimization is simulated. From the simulation, EV demand is satisfied by charging the EV at the lowest price hours and thus shifts the demand peaks to low peak hours. The EV1 user settles the bill with the EV aggregator according to the dynamic pricing of the electricity prices as will be discussed in the following paragraph.

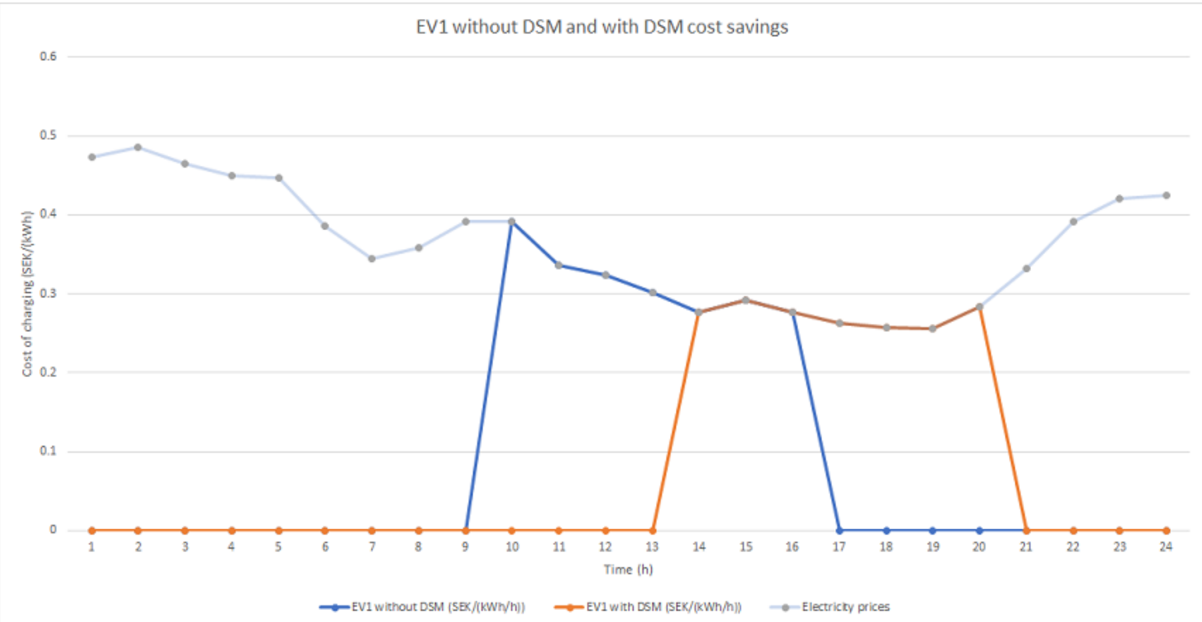

Figure 7.4: Electric Vehicle charging from the grid at cheapest hours

In Fig. 7.5 we have plotted the load profile of the EV user with 24 time slots, where each time slot represents one hour. The blue line represents EV charging without DSM strategy while the orange line represents EV charging with DSM strategies. For the non-DSM curve, the charging starts as soon as the user plugs in the vehicle at 9 AM. From the graph it is evident that the peak demand is at 9 and 10 AM, the low demand time slots are from 14:00 to 20:00 hours. When DSM strategies are included to the simulation, the EV schedules its charging during low demand hours. The EV load is spread across the low demand regions and shift the new peak loads into non-peak hours. It is also evident that shifting the load to cheap hours maximizes the user's payoffs. From the simulation, about 13% is saved in terms of charging cost by shifting the EV energy demand to charge on hours with cheap electricity prices.

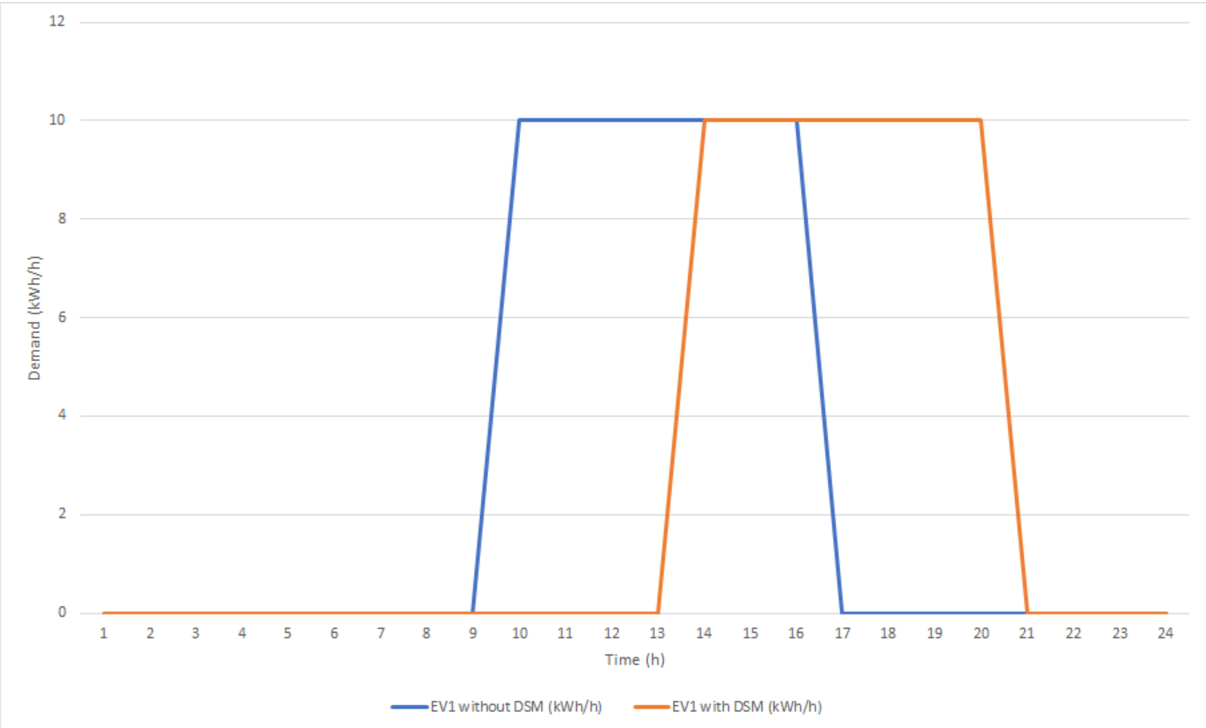

Figure 7.5: Shift of Electric Vehicle charging from the peak demand to low peak hours

The above fig 7.5 shows the shift in the load curve of EV1 from high price hours to low price hours. Since the price directly correlates to the demand at corresponding hours, choosing the cheapest hours would practically flatten the demand profile.

hours	el.price (euro/MWh)	el price (sek/kWh)	li (kwh/h)	Q (kWh/h)	λ (SEK/kWh)
1	46.69	0.4725028	10	10	0.4725028
2	48.04	0.4861648	10	10	0.4861648
3	45.95	0.465014	10	10	0.465014
4	44.45	0.449834	15	15	0.449834
5	44.1	0.446292	15	15	0.446292
6	38.1025	0.3855973	17	17	0.3855973
7	34.04	0.3444848	17	17	0.3444848
8	35.4225	0.3584757	20	20	0.3584757
9	38.695	0.3915934	23	23	0.3915934
10	38.6525	0.3911633	24	24	0.3911633
11	33.145	0.3354274	20	20	0.3354274
12	31.9725	0.3235617	17	17	0.3235617
13	29.7775	0.3013483	18	18	0.3013483
14	27.3	0.276276	20	20	0.276276
15	28.77	0.2911524	20	18	0.3111524
16	27.35	0.276782	20	22	0.256782
17	26.02	0.2633224	20	19	0.2733224
18	25.4	0.257048	20	20	0.257048
19	25.34	0.2564408	20	17	0.2864408
20	27.96	0.2829552	20	23	0.2529552
21	32.76	0.3315312	10	10	0.3315312
22	38.64	0.3910368	12	12	0.3910368
23	41.51	0.4200812	15	15	0.4200812
24	41.99	0.4249388	12	12	0.4249388

Figure 7.6: Table showing the dynamic pricing

The above table shows the assumed values for simulating the dynamic pricing model. The electricity price is taken from Nordpool for sweden SE1 region for the year 2018. The set of 24 hours is randomly taken during spring season. The third column (el price) shows the price of electricity price in SEK/kWh. The fourth column (li) shows the summation of scheduled EV charging at each time slot. The fifth column (Q) is the predicted EV demand computed by the EV aggregator for each time slot for the day ahead-market. Both li and Q values are assumed at random and does not reflect any real case scenario from a grid and EV perspective. The values are chosen to depict the functioning of the non-cooperative game theoretic model and the dynamic price setting. The last column is the computed dynamic pricing from the equation 6.3. The correction factor μ is assumed to be 0.01 to approximate dynamic prices to show in the graph.

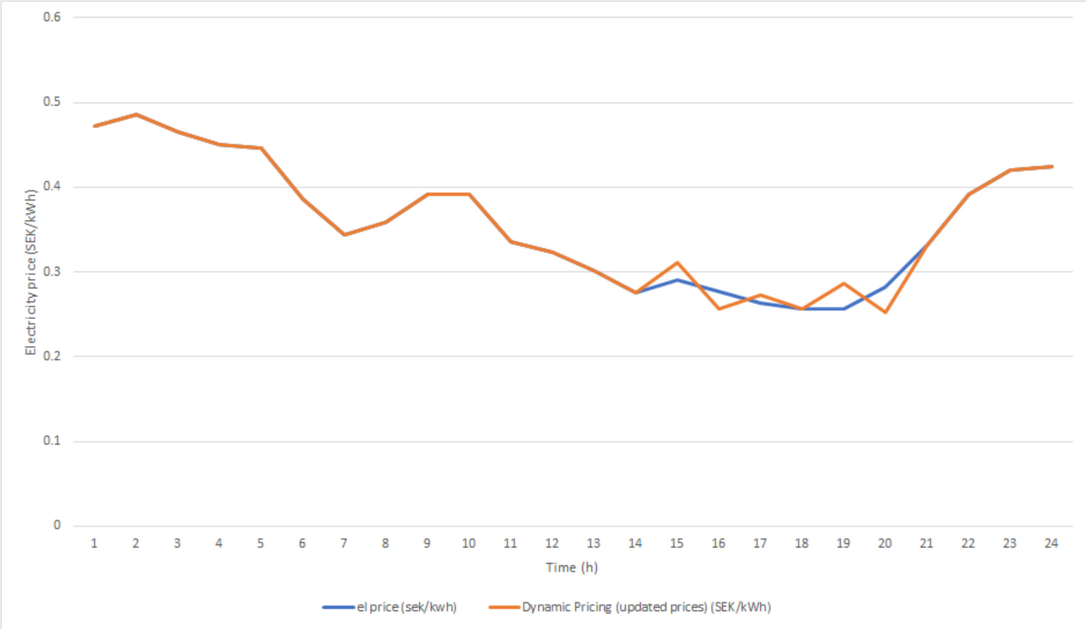

Figure 7.7: Electric Vehicle charging from the grid at cheapest hours

The dynamic pricing reflects and changes according to the number of EV's connected to the grid at scheduled hours to charge. From the graph, it is evident that if the actual demand for the next hour is more than the forecasted demand, the price of electricity increases. This ensures that the peak is not moved to another hour but rather flattens the peaks. By this decentralised EV scheduling mechanism, each EV aims to charge at cheap hours and thereby, the local optimum scales up to give a global optimum of the system, in terms of shifting of peaks and flattening the demand curve.

8

Discussion

Proof-of-concept of a blockchain based P2P EV charging network was developed and tested using three charging scenarios. A smart contract was developed and tested with a set of input parameters to simulate the electric vehicle interaction between prosumers, utility, and V2G within the P2P energy network. An automated smart contract sets the electricity price between the peers. Non-cooperative game theory model is proposed to find the optimal charging schedule for an EV connected to the P2P energy network.

Blockchain technology implementation could enable the prosumers and consumers to manage their demand and trade sustainable energy at cheaper prices. Currently, there are a number of pilot projects with blockchain-based energy platforms that are carried out in the US and other parts of Europe (Andoni et al. 2019). Though various applications stems out of blockchain, a better understanding of the limitations regarding the policy aspects of decentralised data storage is required.

While addressing the P2P capabilities of blockchain, there are certain aspects that need more research and development. One of the main hindrance for blockchain implementation in a smart grid architecture is the handling of the user's data. Unlike traditional centralised databases, the user' data is stored in a decentralised manner in a blockchain interface. Among the greatest challenges faced by P2P energy markets are regulatory constraints (Soto et al. 2020). Currently, the majority of states lack laws and policies that allow for the trading of energy between prosumers. It is therefore vital to validate the P2P model in theory and practice to ensure the government authorities are well informed of the benefits and impacts of the model to make the necessary transition possible (Soto et al. 2020). Furthermore, additional regulations are required to define legal boundaries in order to ensure fairness. For example, legal boundaries of market players, network usage tariffs and users' eligibility for taxing (Esmat et al. 2021). Without these regulations, numerous challenges can arise on the trading platform as well as from unfair and illegal practices.

Moreover, large scale implementation of blockchain based EV charging requires multiple stakeholders to engage and register to the system. The whole success of a P2P network regardless of blockchain implementation depends on the number of peers in the system. Having more users in the system creates more value for the P2P energy network in terms of increased share of individual profits.

8.1 Future Work

For future research it is recommended to focus on integrating other P2P interactions such as vehicle-to-house and PV sharing among houses. The game-theoretic model can be further implemented in establishing the P2P electricity pricing. Additionally, EV aggregators can use machine learning and Artificial Neural Networks to predict the stochastic nature of EV charging patterns and predict the demand curves more precisely. In future, research can also focus on implementing the smart contract in other blockchain platforms such as the hyper- ledger. Moreover, the efficiency and the gas cost of deploying and scaling this platform on a utility level should be further researched. More research should place great emphasis on the adaptation and drafting of new policies to enable P2P energy networks to be implemented on a larger scale.

9

Conclusion

In this thesis, a DSM blockchain framework for P2P electric vehicle charging network has been demonstrated. Firstly, the thesis reviews various academic articles and presents an overview of electric vehicle charging, smart grids, SGAM framework, game theoretical optimisation models, and fundamentals of blockchain technologies. Secondly, the thesis has investigated three scenarios for electric vehicle charging from a prosumer, V2G, and a utility grid perspective. Finally, a consortium blockchain technology is used to design a P2P energy trading market where the consumer, producer and ultimately prosumer, can trade their electricity with each other and the utility grid. A decentralised and distributed trading system is developed using smart contracts that allows a more transparent, trustworthy and secure P2P trading environment. Additionally, the smart contract is responsible for the registration of the users, dynamic charging of the electric vehicle, settling the monetary transaction, and storage of necessary data related to the transactions. To reduce the transmission losses, energy trading based on closest Geo-position data is preferred. The blockchain implementation empowers consumers and prosumers to play a more active role in the energy trading market leading to positive revenue. The thesis proved that the suggested DSM strategy using a blockchain platform shifts the peak load in the electricity grid on a secure and decentralised structure, thereby obtaining a sustainable ecosystem for P2P energy trading between consumers, producers and prosumers. In doing so, more users are provided incentives to make use of sustainable energy whilst most available to reduce intermittency.

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