Serkan SEVEN

A Ph.D. Thesis

AGU 2023

# BLOCKCHAIN BASED PEER-TO-PEER ENERGY TRADING APPLICATIONS

A THESIS
SUBMITTED TO THE DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING
AND THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE
OF ABDULLAH GUL UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

By
Serkan SEVEN
June 2023

# BLOCKCHAIN BASED PEER-TO-PEER ENERGY TRADING APPLICATIONS

A THESIS
SUBMITTED TO THE DEPARTMENT OF ELECTRICAL AND COMPUTER ENGINEERING AND THE GRADUATE SCHOOL OF ENGINEERING AND SCIENCE OF ABDULLAH GUL UNIVERSITY
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

By
Serkan SEVEN
June 2023

## SCIENTIFIC ETHICS COMPLIANCE

I hereby declare that all information in this document has been obtained in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all materials and results that are not original to this work.

Name-Surname: Serkan SEVEN

Signature :

**REGULATORY COMPLIANCE**

Ph.D. thesis titled “Blockchain Based Peer-To-Peer Energy Trading Applications” has been prepared in accordance with the Thesis Writing Guidelines of the Abdullah Gul University, Graduate School of Engineering & Science.

| Prepared By | Advisor |
| --- | --- |
| Serkan SEVEN | Asst. Prof. Gülay YALÇIN ALKAN |

Head of the Electrical and Computer Engineering Program

Assoc. Prof. Zafer AYDIN

## ACCEPTANCE AND APPROVAL

Ph.D. thesis titled "Blockchain Based Peer-To-Peer Energy Trading Applications" and prepared by Serkan SEVEN has been accepted by the jury in the Electrical and Computer Engineering Graduate Program at Abdullah Gül University, Graduate School of Engineering & Science.

08 / 06 / 2023

(Thesis Defense Exam Date)

**JURY:**

Advisor : Asst. Prof. Gülay YALÇIN ALKAN

Member : Assoc. Prof. Ahmet ÖNEN

Member : Asst. Prof. Abdulkadir KÖSE

Member : Asst. Prof. Samet TONYALI

Member : Asst. Prof. Serkan BAHÇECİ

**APPROVAL:**

The acceptance of this Ph.D. thesis has been approved by the decision of the Abdullah Gül University, Graduate School of Engineering & Science, Executive Board dated
/ / 2023 and numbered

/ /

Graduate School Dean
Prof. Dr. İrfan ALAN

# ABSTRACT

# BLOCKCHAIN BASED PEER-TO-PEER ENERGY TRADING APPLICATIONS

Serkan SEVEN
Ph.D. in Electrical and Computer Engineering
Advisor: Asst. Prof. Gülay YALÇIN ALKAN

June 2023

This thesis explores the potential of innovative peer-to-peer (P2P) energy trading schemes for virtual power plants (VPPs) using blockchain technologies, smart contracts, and decentralized finance (DeFi) instruments. Traditional centralized approaches have limitations in terms of transparency and security, which can hinder the successful implementation and operation of VPPs and P2P energy trading systems. The dissertation begins by reviewing the current state of energy sources within the global energy landscape. Understanding the existing landscape provides valuable insights into the potential benefits and challenges of implementing P2P energy trading within VPPs. The focus of the dissertation is to develop and analyze innovative P2P energy trading schemes for VPPs that integrate blockchain technologies and facilities to enhance transparency, security, and automation of energy transactions. Furthermore, DeFi instruments, specifically decentralized exchange (DEX), are used as a novel approach instead of auction methods to determine P2P energy buying and selling prices. Along with blockchain technologies, optimization is used to maximize the economic benefits of peers. The sequential decision problem of the trading schemes is solved with mixed integer linear programming (MILP). In addition, machine/deep learning models are utilized to overcome the drawbacks of conventional mathematical programming like MILP. These models can accelerate the decision-making processes by learning from the optimization results obtained. Overall, frameworks for the successful integration of P2P energy trading within and among VPPs are developed to validate the effectiveness and feasibility of the proposed P2P energy trading schemes through case studies and simulations using realistic data sets and blockchain platforms.

*Keywords: Blockchain, Smart Contract, Peer-to-peer energy trading, Virtual Power Plant, Decentralized Exchanges*

# ÖZET

# BLOKZİNCİR TABANLI EŞTEN-EŞE ENERJİ TİCARETİ UYGULAMALARI



Serkan SEVEN
Elektrik ve Bilgisayar Mühendisliği Anabilim Dalı Doktora
Doktora Tez Yöneticisi: Dr. Öğr. Üyesi Gülay YALÇIN ALKAN
Haziran-2023



Bu tez, blokzincir teknolojileri, akıllı sözleşmeler ve merkezi olmayan finans (MOF) araçlarını kullanarak sanal enerji santralleri (SES) için yenilikçi eşten-eşe enerji (EEE) ticaretinin potansiyelini araştırmaktadır. Geleneksel merkezi yaklaşımlar şeffaflık ve güvenlik açısından sınırlamalara sahiptir ve bu da SES ve EEE ticaret sistemlerinin başarılı bir şekilde uygulanmasını ve işletilmesini engelleyebilir. Bu tez, enerji kaynaklarının küresel ölçekteki durumunu gözden geçirerek başlamaktadır. Mevcut manzaranın anlaşılması, SES içinde EEE ticaretinin uygulanmasının potansiyel faydaları ve zorlukları hakkında değerli bilgiler sağlamaktadır. Tezin amacı, enerji ticaretinin şeffaflığını, güvenliğini ve otomasyonunu artırmak için blokzinciri teknolojilerini ve olanaklarını entegre eden SES için yenilikçi EEE ticareti planlamaları geliştirmek ve analiz etmektir. Ayrıca yeni bir yaklaşım olarak, açık artırma yöntemlerinin yerine MOF araçları özellikle de merkezi olmayan borsa, EEE alış ve satış fiyatlarının belirlenmesinde kullanılmaktadır. Blokzincir teknolojileri ile birlikte, eşlerin ekonomik faydalarını en üst düzeye çıkarmak için optimizasyon kullanılmıştır. Ticaret planlarının sıralı karar problemi, karışık tamsayılı doğrusal programlama (KTDP) ile çözülmektedir. Buna ek olarak, KTDP gibi geleneksel matematiksel programlamanın dezavantajlarının üstesinden gelmek için makine/derin öğrenme modelleri kullanılmaktadır. Bu modeller, elde edilen optimizasyon sonuçlarından öğrenerek karar verme süreçlerini hızlandırabilmektedir. Genel olarak, SES içinde ve arasında, EEE ticaretinin başarılı bir şekilde entegrasyonu için blokzinciri platformları kullanılarak gerçekçi veri setleri, vaka çalışmaları ve simülasyonlar yoluyla önerilen EEE ticareti planlamalarının etkinliğini ve fizibilitesini doğrulamak için çerçeveler geliştirilmiştir.



*Anahtar kelimeler: Blokzincir, Akıllı sözleşme, Eşler arası enerji ticareti, Sanal Enerji Santrali, Merkezi olmayan borsalar*

# Acknowledgements

I would like to express my gratitude to my advisor for her time, support, patience, and valuable assistance throughout the study, especially in bureaucratic processes.

Assoc. Prof. Ahmet ÖNEN was instrumental in guiding me to complete the thesis. I am very grateful for the opportunity to work with him and for his insightful support throughout.

With the same level of gratitude, I would also like to thank the entire thesis committee members and juries, including the replaced ones, for their valuable time, comments, and understanding. In addition, I would like to thank all my colleagues who have supported me directly or indirectly during this long period that once seemed to me to never end.

Finally, I owe a deep debt of gratitude to everyone who has supported and encouraged me in my personal life. Especially to my precious mother, father, and younger sister for their endless support throughout my life, and to the grandfathers and grandmothers who have passed away.

# TABLE OF CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# LIST OF ABBREVIATIONS

| | |
|---|---|
| AB | Avalanche Bridge |
| ABI | Application Binary Interface |
| AET | Average Execution Time |
| AMM | Automated Market Maker |
| CEX | Centralized Exchange |
| CFMM | Constant Function Market Maker |
| DApp | Decentralized Application |
| DeFi | Decentralized Finance |
| DER | Distributed Energy Resources |
| DEX | Decentralized Exchange |
| DL | Deep Learning |
| DSO | Distribution System Operator |
| EMS | Energy Management System |
| ESS | Energy Storage System |
| ETC | Energy Trading Coordinator |
| ETH | Ether, Ethereum |
| EV | Electric Vehicle |
| EVM | Ethereum Virtual Machine |
| GAMS | General Algebraic Modeling System |
| HTTP | Hyper Transfer Protocol |
| ICT | Information and Communication Technology |
| IDE | Integrated Development Environment |
| IEA | International Energy Agency |
| IoT | Internet of Things |
| KNN | k-Nearest Neighbors |
| LP | Liquidity Provider |
| LR | Linear Regression |
| MG | Microgrid |
| MILP | Mixed Integer Linear Programming |
| ML | Machine Learning |

| | |
|---|---|
| P2G | Peer-to-grid |
| P2P | Peer-to-peer |
| PoS | Proof-of-Stake |
| PoW | Proof-of-Work |
| PV | Photovoltaic |
| RES | Renewable Energy Sources |
| RS | Running Scheme |
| SC | Smart Contract |
| SVM | Support Vector Machine |
| TG | Total Generation |
| TL | Total Load |
| TRY | Try Energy Token |
| TSO | Transmission System Operator |
| TVPP | Technical Virtual Power Plant |
| VM | Virtual Machine |
| V2G | Vehicle-to-grid |
| V2H | Vehicle-to-home |
| V2V | Vehicle-to-vehicle |
| VPP | Virtual Power Plant |
| Web3.js | Ethereum JavaScript API |

*To my family*

# Chapter 1

# Introduction

Population growth, economic development, and energy availability have increased global energy demand during the past decade. However, growth rates vary by geographic region and energy type. The quantity of energy necessary to fulfill the demands of all sectors requiring energy, such as the generation of electricity, transportation, and other areas, is referred to as the total primary energy demand. As per the report from International Energy Agency (IEA), the world's total primary energy demand rose by more than 10% between 2010 and 2019 and is expected to continue to increase in the coming decades, but at a slower pace than in the past owing to efforts to enhance energy efficiency and transition to low-carbon energy sources. Based on current policy commitments and announced government plans around the world, the IEA's "Stated Policies Scenario" forecasts a 25% increase in global total primary energy demand from 2020 to 2040. However, if more ambitious climate policies are implemented to reach the goals of the Paris Agreement, the global total primary energy demand could plateau in the 2030s and begin to decline thereafter. In terms of energy sources, the IEA expects that renewable energy sources (RESs) (including solar, wind, hydropower, and bioenergy) will account for the largest share of new energy demand growth over the next two decades, followed by natural gas. The share of coal in the global energy mix is expected to decline, although it will remain an important source of energy in some regions [1], [2].

There is a vicious cycle between fossil fuel use for electricity generation, and the impacts of climate change on the electricity system. Burning fossil fuels releases greenhouse gases, which contribute to climate change by trapping heat in the Earth's atmosphere, causing temperatures to rise and altering weather patterns, sea levels, and other climatic phenomena. This, in turn, impacts the reliability and efficiency of the electricity system. For example, extreme weather events such as heatwaves, droughts, and storms can damage power plants and transmission lines, causing power outages and disruptions to energy supply. Sea level rise and coastal erosion can also damage infrastructure located in coastal areas. These impacts can subsequently make it more difficult to generate and distribute electricity, which can lead to further reliance on fossil fuels as backup energy sources.

As of 2021, the majority of the world's energy still comes from fossil fuels, such as coal, oil, and natural gas. However, the use of RESs, such as wind, solar, and hydropower, has been increasing in recent years. The exact percentage of the energy mix varies by country and region, but globally, it is estimated that approximately 80% of the world's energy consumption still comes from fossil fuels, while approximately 20% comes from renewable sources. Nevertheless, the share of renewable energy is expected to grow in the coming years as new approaches and mechanisms for the energy sector emerge [3]. More ambitious energy and climate legislation, technical advancements, and heightened energy security concerns are driving the shift to sustainable energy [4]. In 2022, clean energy investment reached USD 1.4 trillion, up 10% from 2021 and accounting for 70% of the increase in total energy sector investment. Despite this significant advancement, fossil fuels (oil, coal and low-carbon sources) continue to make up substantial portion of the primary energy mix [5]. Figure 1.1 depicts the relative contributions of fossil fuels (low-carbon and coal), nuclear, and RESs to global electricity generation over a 50-year period, from 1971 to 2021. As this figure shows, the growth of solar and wind has been noticeable in the previous decades. Our reliance on fossil fuels remains critical for electricity generation. Solar photovoltaic (PV) and wind seemingly will dominate the expansion of renewables in the electricity market over the next few decades.

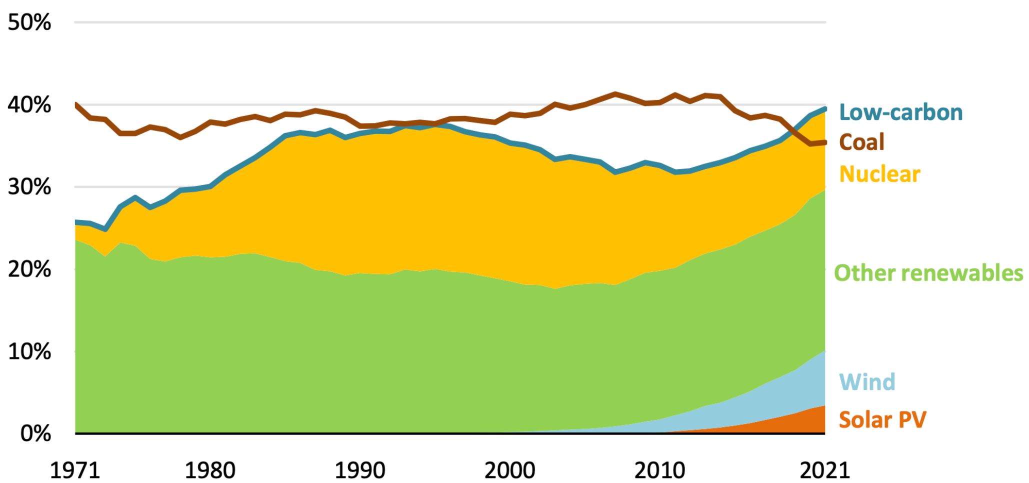


**Figure 1.1 Share of low-carbon sources and coal in world electricity generation** [3].

There has been a substantial uptick in the utilization of RESs and distributed energy resources (DERs) in recent years, as the world increasingly prioritizes sustainable energy solutions. The urgent need to combat climate change, lessen reliance on fossil fuels, and guarantee reliable energy supplies is behind this transition. Ingenious strategies for DER integration into the electricity grid are required to realize these objectives.

Incorporating Virtual Power Plants (VPPs) is one such strategy; these platforms aggregate and manage the capabilities of DERs such as solar PVs, wind turbines, and energy storage systems (ESSs). In addition, with the imminent inclusion of electric vehicles (EVs) can greatly support VPPs by providing additional flexibility, storage capacity, and demand response. This integration can be achieved through vehicle-to-grid (V2G) technology, which allows EVs to interact with the grid, supplying electricity during peak demand periods and absorbing excess energy when needed. By combining the output of these resources, VPPs can effectively act as a single, flexible, and responsive power plant, enabling them to optimize energy production, consumption, and grid stability. Thus, P2P energy trading in local communities become feasible between VPPs and within the VPPs.

## 1.1 Evolution of P2P Energy Trading

P2P energy trading represents a transformative approach to traditional centralized energy markets. This approach is driven by the proliferation of DERs, the advancement of information and communication technologies (ICT), and the growing demand for environmentally responsible and sustainable energy solutions. P2P energy trading possesses the capacity to revolutionize the energy industry. Historically, the energy sector has been a centralized model, using extensive transmission and distribution networks to transfer electricity generated by large-scale power plants to end-users. The emergence of DERs, including but not limited to PV solar panels and wind turbines, has resulted in the development of P2P energy trading. The aforementioned structure enables prosumers to produce and consume electricity amongst their respective local communities.

Blockchain and its associated technologies hold significant promise in enabling P2P trading. These technologies can establish a secure and transparent framework for transactions between prosumers. Blockchain technology, which is a distributed and decentralized ledger, has the potential to effectively manage and record energy transactions. By eliminating single point of failure and reducing intermediary expenses, decentralization fosters a more robust and cost-effective system. All transactions recorded on the blockchain are viewable by all participants, ensuring a high level of transparency and nurturing trust among prosumers in the P2P energy market. The data is encrypted and tamper-proof, making blockchain a secure platform for energy transactions. This security can safeguard the P2P energy trading system from fraudulent activities and data manipulation, ensuring its integrity. Smart contracts in blockchain are self-executing agreements with the contract terms directly coded into them. Through the utilization of smart contracts, P2P energy trading platforms can automate transactions, allowing for the settlement of trades in real time and reducing the need for manual intervention. This automation can improve the energy trading process's efficacy, speed, and error-prevention. Blockchain technology can eliminate the need for a centralized intermediary to validate and administer energy transactions. In the context of P2P energy trading, several intermediary actors could be involved in the process aside from utility companies. Some of these actors include:

1. Energy retailers: These entities are responsible for selling electricity to consumers. They often act as intermediaries between energy producers and consumers, managing contracts, billing, and customer support. In a blockchain-enabled P2P energy trading system, the role of energy retailers could be diminished as consumers could trade energy directly with each other.
2. Distribution system operators (DSOs): DSOs are responsible for maintaining and operating the distribution networks that deliver electricity to consumers. They are also in charge of connecting energy producers and customers. DSOs might still play a role in grid infrastructure maintenance under a decentralized energy trading paradigm, but their position as a middleman in energy transactions could be minimized.
3. Transmission system operators (TSOs): TSOs are responsible for overseeing and managing the high-voltage transmission grids that allow electricity to travel long distances. They ensure the stability of the grid and balance supply and demand. While TSOs may still be necessary for grid management, their role as an intermediary in P2P energy trading could be diminished.
4. Energy service companies (ESCOs): ESCOs provide energy efficiency services (and also renewable energy services), demand response programs, and other services aimed at optimizing energy consumption. In a decentralized energy

market, these companies may need to adapt their business models to work with P2P trading platforms and blockchain-based systems.

5. Meter data management providers: These companies collect, validate, and process meter data to calculate energy consumption and production for billing purposes. With blockchain-enabled P2P energy trading, meter data management could become decentralized and automated, reducing the need for these intermediaries.
6. Energy brokers and aggregators: Energy brokers help consumers find the best energy deals, while aggregators bundle together energy from multiple producers to sell in the wholesale market. Both roles could be disrupted in a decentralized P2P energy trading environment, where consumers and producers can trade energy directly with one another.
7. Regulatory bodies and government agencies: These entities oversee energy markets, establish rules, and ensure compliance. While regulatory bodies will still have a role in ensuring safety and fairness in a decentralized energy market, their functions may evolve as the market becomes more reliant on blockchain-based systems and P2P transactions.

The transition to a decentralized P2P energy trading market may reduce or eliminate the need for some of these intermediary actors. However, this will depend on the development and adoption of blockchain-based solutions, regulatory support, and the ability of these actors to adapt to new technologies and business models. By leveraging the power of blockchain technologies and smart contracts, P2P energy trading platforms can transform the way energy is produced, consumed, and traded. This transformation has the potential to empower prosumers, increase the adoption of RESs, and contribute to a more sustainable and resilient energy system.

## 1.2 Blockchain Networks in P2P Energy Trading

Blockchain is a distributed network of interconnected nodes. Thanks to these distribution, cryptographic techniques, and consensus algorithms, blockchain can keep digital information secure and unalterable. Blockchain technology is being used more and more for P2P energy sharing, which makes people capable of trading energy directly without the need for middlemen. P2P energy trade platforms can be built on public, private, or consortium blockchain networks, each of which offers different levels of access, control, and collaboration. Here's an overview of P2P energy trading in the context of the three main types of blockchain networks:

1. Public blockchains: These are also referred to as permissionless blockchains. A P2P energy trading platform built on a public blockchain enables anyone to join the energy market. Participants can buy, sell, or trade energy without needing permission from a central authority. This arrangement can potentially boost competition and lower costs since energy transactions occur directly between consumers and producers. However, public blockchains may encounter challenges related to scalability, transaction speed, and privacy, all of which are crucial factors in energy trading systems. Bitcoin and Ethereum are notable examples of public blockchains that use consensus algorithms such as Proof of Work (PoW) or Proof of Stake (PoS) to validate transactions and ensure network security.
2. Private blockchains: Often called permissioned blockchains, these limit participation to a specific group of organizations or individuals. A central authority controls access to the network, managing read and write permissions, and allowing only authorized users to view the data. This setup provides a higher level of privacy and control over the network, at the expense of losing decentralization. Private blockchains are typically used by organizations that want to benefit from the security and transparency of blockchain technology while maintaining control over who can access and modify the data. Examples of private blockchain platforms include Hyperledger Fabric and R3's Corda.
3. Consortium blockchains: Also known as federated blockchains, are a hybrid between public and private blockchains. Consortium blockchains can be an effective solution for P2P energy trading among multiple organizations, such as utility companies, energy producers, and regulatory bodies. By distributing control among trusted participants, consortium blockchains can facilitate collaboration and data sharing while maintaining security and transparency. This model allows different stakeholders to work together in managing the energy market, making decisions, and setting rules for P2P trading. Examples of consortium blockchains include Quorum and Hyperledger Besu.

In summary, the choice between public, private, and consortium blockchains for P2P energy trading depends on the desired level of openness, control, and collaboration among participants. Public blockchains offer a more open and competitive market but may face scalability and privacy challenges. Private blockchains provide greater control and privacy but may limit competition and openness. Consortium blockchains strike a balance, allowing multiple organizations to collaborate securely and transparently in managing the energy market.

## 1.3 Motivation and Problem Statement

The research in this thesis is driven by the significant impetus to tackle the challenges of effective energy management and P2P trading in VPPs and microgrids through the utilization of blockchain technologies. Traditional centralized approaches to energy trading and management have limitations in terms of scalability, transparency, and security, which can hinder the successful implementation and operation of VPPs and P2P energy trading systems.

The problem statement for this research can be summarized as follows: How can novel P2P energy trading schemes for VPPs, using blockchain technology, smart contracts, decentralized finance (DeFi) instruments, and machine learning (ML)/deep learning (DL), improve the efficiency, security, and cost-effectiveness of energy transactions among DERs and electric vehicles (EVs)? To address this problem, the thesis aims to develop and analyze innovative P2P energy trading schemes for VPPs, with a focus on the following key aspects:

- Enhancing the transparency, security, and automation of energy transactions with blockchain and smart contracts.
- The utilization of DeFi instruments and decentralized exchange (DEX) for facilitating P2P energy trading within and between VPPs.
- The application of ML/DL models in optimizing energy trading processes, with the goal of improving the scalability and efficiency of P2P energy trading in microgrids.
- The evaluation of the proposed P2P energy trading schemes regarding contribution to global sustainability goals and their potential societal impact and environmental benefits.

## 1.4 Objectives and Contributions

The main objective of this thesis is to offer a thorough comprehension of blockchain based P2P energy trading applications within and between local communities and agents, emphasizing its assimilation within VPPs and its consequences for DERs and EVs. In other words, the aim is to help broaden the perspective of P2P energy trading, which will become more prevalent in the near future through the use of blockchain and its related technologies as well as smart systems and algorithms.

The increasing integration of RESs and DERs in power systems presents both opportunities and challenges for optimizing energy management and trading. The emergence of VPPs and P2P energy trading has paved the way for more efficient and decentralized energy systems. This thesis aims to explore the potential of novel P2P energy trading schemes in VPPs, employing cutting-edge technologies such as blockchain, smart contracts, DeFi instruments, and ML/DL models. The main points of the thesis are described by the following objectives:

- To review and analyze the current state of RESs, DERs, VPPs, and EVs in the global energy landscape, highlighting their significance and potential for future growth.
- To investigate the existing literature on P2P energy trading, including its underlying technologies, market mechanisms, and various models, to establish a solid foundation for further exploration.
- To examine the economic, social, and environmental benefits of P2P energy trading within local communities, particularly in terms of energy efficiency, cost savings, and emission reduction.
- To propose a framework for the successful integration of P2P energy trading within VPPs, considering the technical, economic, and security aspects.
- To evaluate the potential of P2P energy trading in enhancing the role of DERs and EVs in the energy system, as well as its impact on grid stability and resilience.
- To develop and analyze innovative P2P energy trading schemes for VPPs utilizing blockchain technology, smart contracts, and DeFi, to improve the efficiency, security, and cost-effectiveness of energy transactions.

- To find out how DEX can help P2P energy trading between VPPs and how ML/DL can be used to improve energy trading processes, with the goal of making P2P energy trading in microgrids more scalable and efficient.
- To assess the contributions of the proposed P2P energy trading schemes to the broader goals of sustainability, specifically in relation to the United Nations' Sustainable Development Goals (SDGs), and to discuss the potential societal impact and environmental benefits of implementing these systems.
- To validate the feasibility of the proposed P2P energy trading schemes through case studies and simulations using realistic data sets and the Ethereum Virtual Machine (EVM) based blockchain platforms such as Ethereum and Avalanche.

The scope of this thesis is primarily focused on P2P energy trading within local communities. While other types of energy trading, such as wholesale, feed-in-tariff or utility-scale trading, may share some similarities with P2P energy trading, they are beyond the scope of this study. Furthermore, the analysis will primarily concentrate on the technical, economic, and security aspects of P2P energy trading, rather than the regulatory aspects and specific social or cultural factors that may influence its adoption in various communities.

## 1.5 Thesis Outline

The remainder of the thesis is organized as follows:

The second chapter proposes a novel P2P energy trading scheme for a VPP using smart contracts on the Ethereum blockchain platform and presents the related literature. The chapter focuses on the financial aspects of P2P trading in a VPP framework and develops a P2P energy trading mechanism and bidding platform based on a public blockchain network. The proposed scheme operates an auction by smart contracts addressing both cost and security concerns. Finally, the proposed architecture is validated using realistic data with the Ethereum Virtual Machine (EVM) environment of Ropsten Test Network. This chapter was published in the journal of IEEE Access [6].

The third chapter introduces an inter-VPP peer-to-peer (P2P) trading scheme utilizing the Avalanche blockchain platform and presents the related literature. Moreover, the chapter describes the merits of DeFi contributing significantly to the workflow in this type of energy trading scenario. Finally, a detailed case study is used to examine the effectiveness of the proposed scheme and flow, and important conclusions are drawn. This chapter was published in the journal of Sustainability [7].

In Chapter 4, a new approach to optimize peer-to-peer energy trading among Virtual Power Plants by combining Mixed Integer Linear Programming with Machine/Deep Learning models is presented. The approach accounts for Decentralized Exchange swaps and token pair value changes to minimize energy trading costs. To improve scalability and efficiency, ML/DL models are used to solve subsequent optimization problems faster. Overall, this approach aims to create a sustainable and decentralized energy system by improving P2P energy trading in microgrids.

Finally, Chapter 5 summarizes the main contributions and findings of this thesis, along with some final remarks. Moving forward, future research directions for improving and expanding upon these approaches have also been identified.

# Chapter 2

# Peer-to-Peer Energy Trading in Virtual Power Plant Based on Blockchain Smart Contracts

A novel Peer-to-peer (P2P) energy trading scheme for a Virtual Power Plant (VPP) is proposed by using Smart Contracts on Ethereum Blockchain Platform. The P2P energy trading is the recent trend the power society is keen to adopt carrying out several trial projects as it eases to generate and share the renewable energy sources in a distributed manner inside local community. Blockchain and smart contracts are the up-and-coming phenomena in the scene of the information technology used to be considered as the cutting-edge research topics in power systems. Earlier works on P2P energy trading including and excluding blockchain technology were focused mainly on the optimization algorithm, Information and Communication Technology, and Internet of Things. Therefore, the financial aspects of P2P trading in a VPP framework are focused and, in that regard, a P2P energy trading mechanism and bidding platform are developed. The proposed scheme is based on public blockchain network and auction is operated by smart contract addressing both cost and security concerns. The smart contract implementation and execution in a VPP framework including bidding, withdrawal, and control modules developments are the salient feature of this work. The proposed architecture is validated using realistic data with the Ethereum Virtual Machine (EVM) environment of Ropsten Test Network.

## 2.1 Introduction

Distributed generation is electricity production from variety of distributed energy resources (DER) such as rooftop solar photovoltaic (PV) units, wind generating units, open and closed cycle gas turbines, diesel generators, hydro or mini-hydro schemes, and battery storage. In contrast to the conventional electric power systems, distributed generation is alterable, amenable, acentric, and customizable owing to its structure adjacent to the ultimate consumer spot. DER are mostly arranged in microgrids which are being either connected or disconnected from grid [8].

Microgrids consist of localized set of power sources, loads, and DER. In few last decades, the notion of microgrids had been becoming more common and many microgrids operated in such a way to use energy effectively and efficiently. Some studies have been conducted to integrate DER into grid while guaranteeing system operations satisfactorily [9], [10]. The Virtual Power Plant (VPP) concept has been raised afterward to be able to incorporate DER into the grid enabling bi-directional power and information exchanges without affecting grid reliability and stability, utilizing the blessings of Information and Communication Technology (ICT) [11]. It is theoretically used for aggregation of DER, so that they can serve as a fully dispatchable unit managing information from a wide variety of physical infrastructures such as wind, hydro, solar photovoltaics (PVs), Energy Storage Systems (ESSs), market operation, and distribution system operator (DSO).

Majority of the electricity customers, known as consumers in microgrid, VPP, and power system are connected with typical centralized energy trading systems where the energy trading is handled in wholesale markets regulated by the transmission system operator (TSO). On the other hand, the modern power systems including microgrid and VPP accommodate many DERs where the concept of energy consumers has been changed as prosumers, who can conceptually produce and consume energy. The generation of electrical energy by the components of DERs is stochastic and intermittent; therefore, the prosumers of the VPP who have surplus energy can store it if they have energy storage systems or sell it to the grid or other parties. This transaction of energy among prosumers is called Peer-to-Peer (P2P) energy trading [12]. In the smart grid framework, the energy trading algorithms are becoming important factors to fulfill the energy demand requirements considering the unpredictable generation pattern of DERs. These days, game theory has been identified as a potential analytical tool for energy trading and sharing in microgrid and smart grid which mathematically allows solving optimization problems with multi-objective functions [13]–[18]. A new scalable market design for P2P energy trading through bilateral contract networks is reported in [19]. In [20], an incentive prosumer based P2P energy trading is proposed.

It appears that P2P energy trading in VPP framework is relatively new and most of the reported works are either in the conventional ICT domain or using optimization algorithm to handle unpredictability of microgrid operations. Only few works and real-world projects in microgrid and VPP domain are focused on decentralized mechanism using public blockchain technology. In this work, a novel VPP architecture has been developed to enable P2P energy trading mechanism with auction-based bidding model using smart contracts and priority was given to explain the stages of development and implementation over Public Ethereum Platform. Unlike others, this platform can be used among other VPPs and intra-VPPs since public blockchain is used, and it is relatively scalable and less costly compared to ICT operations needed for private blockchain usage for every single VPP. Because there is no need for keeping in-house servers and nodes up to create a private blockchain network. Essentially, the need for intermediary authorities such as aggregators in the use of private blockchain undermines the true decentralization and transparency concept of P2P trading. To reach that adaptivity, in this article, public blockchain environment is chosen over private and consortium (permissioned) blockchain networks because of high initial cost and limitations on physical structure, respectively.

The proposed platform is implemented based on the needs of the VPP framework and includes several modifiable mechanisms for easy adaptation to the different inter- or intra-operations of VPP operators. In the auction mechanism, bidding, withdrawal, and control modules are developed to show the operability of the platform. Three different running schemes (RS) are considered and proposed also to address centralization, cost and security measures in P2P energy trading. A complete smart contract platform and real-life cryptographic testing environment have been realized using EVM, Remix, Metamask, Web3.js, Infura.io, Ropsten and the P2P energy trading in VPP is verified using realistic generation and load data. The contributions of the paper can be summarized as follows:

- The proposed solution of P2P energy trading is solely for VPP architectures and new in VPP domain.
- The implementation part is demonstrated step by step by integrating power system and blockchain ecosystem, as well as presenting several running schemes.
- A modular smart contract mechanism is proposed which can be used effectively in P2P energy trading within VPP framework. Thus, each module can be improved and be easily adapted to several other use cases.

- Usage of public Ethereum network instead of private or consortium network and modular approach to VPP framework to make it applicable to both intra and inter VPPs; systematic way to implement smart contract to enable P2P trading, development of bidding, withdrawal, and control modules by properly integrating power system and computing software are the novel contributions of this article.
- Therefore, unlike other studies, the proposed framework and approach in this article is able to be adapted and converted easily to Decentralized Application (dApp) which is the cutting-edge usage of smart contracts and blockchain. DApps are expected to be an important part of the new era in the world-web history, which is named as Web 3.0.

## 2.2 Modern Energy Trading Approaches and Background

Currently, there are quite a few projects and initiatives enabling trading between consumers and prosumers possible in microgrids by the help of the conventional ICT, mostly using client-server architecture [21]. Most of the energy management and trading platforms had been created by using these technologies are aiming general wholesale or retail business models [22]. Correspondingly Porto and US based two initiatives with the same name as Smartwatt, UK based Piclo, Netherlands based Vandebron and German project Smart Watts can be given as examples and these systems attempt to reach economic efficiency by making the trading easy and optimized [23]–[26]. Furthermore, Sonnen community [23] set their goal as sharing and trading energy in order to fulfil energy needs from RES in a decentralized manner. Therefore, it is easy for one to interfere that the inclination in the power market is towards P2P sharing and trading. Because eliminating the intermediaries brings efficiency to the grids in terms of time, cost, and effort spent.

Potential instances of P2P usage include decentralized trading, i.e., mutual trading among prosumers, consumers, and conventional power suppliers. Hence, PeerEnergyCloud project’s objective in Germany was making research and development of cloud-based technologies for such a concept [27]. This covers the creation and the implementation of an advanced recording and prediction methodology to address the local excessive energy production issue, including a virtual marketplace for local energy trading.

While above-mentioned industrial projects are mostly the traditional server-centric and have a central authority to control the operation, energy trading efforts migrate towards blockchain since the intrinsic decentralizing nature of the blockchain architecture is consistent with the decentralized P2P trading. As a matter of fact, London-based energy technology company Electron [28] developed an energy metering and billing platform using blockchain. And TransActiveGrid, which afterwards took place under the umbrella of US-based energy technology start-up LO3 [29], established Brooklyn Microgrid successfully as the first P2P energy trading project within microgrids by using blockchain [30]. Blockchain based P2P energy trading companies akin to Power Ledger were established and projects similar to White Gum Valley project were realized in Australia [31]. The country has great potential for decentralized P2P trading thanks to its solar insolation, wind power sources and its relatively high-cost grid-sourced electricity [32].

There are several power-based applications that leverage blockchain platforms including data exchange scenarios between smart devices, digital P2P transactions, machine-to-machine (M2M) communication, business-to-business (B2B) energy trading, mutual transactions between prosumers and consumers in transactive energy networks, smart home, electric vehicle (EV), and microgrid development scenarios [33].

The usage of blockchain can contribute to fulfilling the strict security and privacy requirements of the IoT systems for local electricity storage systems. Hence, significant research studies focused on anonymous payment and safeguarding peers or EV owners' privacy on the trading platform. Kang et al. [34] have come up with a localized P2P electricity trading system with consortium (permissioned) blockchain. Trading among plug-in hybrid electric vehicles (PHEVs) in smart grid is realized with an iterative double auction mechanism. In [35], a security model for trading between EVs and charging pile management on the blockchain that leverages the lightning network and smart contract technologies was focused. A decentralized energy trading system with blockchain was presented using multi-signatures to enable peers to perform transaction anonymously and securely [36]. In [37], a credit-based payment scheme and a Stackelberg game based optimal pricing strategy were proposed to support the scalability of transactions. A consortium blockchain is used for the security concerns. A local energy market operated with a double auction system that uses a smart contract on a private Ethereum blockchain to determine the market closing hours have been developed [38]. Nonetheless, limited information regarding the implementation of the smart contract and how the price is cleared during each trading session was given. An energy-trading system has been developed using consortium blockchain so that it could be secure and privacy-preserving in the smart grid [39]. In [40], a blockchain based P2P energy trading and crowdsourcing architecture with an optimization model is developed. In [41], all transactions are stored on a consortium blockchain which is generally supervised by some kind of aggregators or energy traders and the financial institutions that support anonymous payment. In [42], P2P transactions between EVs and grid, and among EVs realized with an EV power trading model based on private Ethereum blockchain and smart contract, considering the randomness and uncertainty of the EV charging and discharging. A reverse auction mechanism based on a dynamic pricing strategy and aggregators is used. In [18], a P2P energy trading scheme with the cooperative Stackelberg game formulation was proposed to help a centralized power system to reduce the total electricity demand at the peak hour. Price-based control of DERs to support the grid is also a matter of concern in VPP-related literature. Di Silvestre et al. [43] studied ancillary services in the energy blockchain for microgrids and focused mainly on the technical issues related to power transmission. In [44], again it's focused on secure and verifiable energy trading with blockchain. In the study, it's emphasized that the blockchain should provide transparency, immutability, and auditability to the energy trading. A consortium blockchain based scheme was proposed to block energy sellers refusing to transfer the negotiated energy to the purchaser. In [45], a consortium blockchain is used to design a hybrid P2P energy trading market where consumers and prosumers trade each other and with the main grid. Although the study clearly elaborates on the concepts of P2P trading in a smart grid environment, it lacks the implementation details regarding blockchain and smart contracts and shows simulation results with local machine development tools of Ethereum. Han et al. [46] proposed a private Ethereum based smart contract architecture with the conventional double auction. A smart contract consisting of four core algorithms has been developed; the purpose of each algorithm is to save gas consumption and ensure security. Performance measures are given, energy trading supports 25 agents at the same time, with more than six miner nodes. In [47], introduces a private Ethereum blockchain based energy trading architecture for EVs within smart cities. It is not a clean slate approach and builds on to the existing infrastructure. Although transparency brought by blockchain is praised, the private version is used because it is considered to be more efficient than the public version. Also, it is noted that executing a large number of transactions causes a serious computational load.

In some scenarios, security can be the bottleneck due to the variety of the participants, however, in some cases, the architecture and transparency could be the key point for the platform. Please note that, unlike the trading environment of EVs, in a VPP environment agents are mostly stationary and naturally, there is a limitation for participating in the blockchain network because of the physical requirements i.e., power lines and infrastructure. Also, all the participants and roles are needed to be known by the VPP admin, which eliminates the random users, to assure connectivity and reliability for distribution network. Therefore, even if the public blockchain is used for the trading system, it is being restricted by the physical conditions, and benefiting the advantages of the public network simultaneously.

According to the survey published by German Energy Agency, in power market and electricity value chain establishing smart contracts can be utilized for demand response services, cooperation and control of VPPs, grid and network, governance of energy storage systems, control of decentralized energy systems, community energy projects, and coordination of RES power plant portfolio [48]. There are some concerns and costs regarding the adaptation of the current power infrastructure to work with blockchain and smart contracts, i.e., deploying compatible smart meters and Internet of Things (IoT) appliances. However, the business processes for energy trading can likely be reconstructed by this trend, together with the capability of automation and big data analytics. Using this information analysis could yield to demand aggregation and response services being optimized, could promote VPPs, and possibly improve the involvement of active consumers, prosumers, and renewable energy.

This study is focused to resolve the business processes associated with P2P energy trading of VPP.

## 2.3 Blockchain and Smart Contract

In the last decade, when the P2P money transaction is introduced in [49] without any intermediary authority such as banks, many cryptocurrencies mushroomed. The technology behind the cryptocurrencies, known as the Blockchain, leads many other future promising applications as well [50]. Blockchain is a distributed platform with interconnected blocks which constitute a vast immutable digital ledger in the end. The integrity and consistency of transactions are protected by cryptographic mechanisms such as hash functions, asymmetric encryption (public-key cryptography), and Merkel-trees

[51]. All the transactions are kept on the blocks just like the traditional bank records with the difference of generating a distributed universal public ledger eventually. Every block, except the first one known as genesis block, points out the previous block with its hash in order to create a chain of blocks. The entire system is based on a P2P network. Nodes keep the database distributed and decide which transactions will be approved. Since they work for the liveliness of the system, participants get rewards, which is called mining. Therefore, the blockchain becomes a very distinctive kind of immutable distributed large-scale database and used in several fields in addition to finance. Ethereum is one of these blockchain-based platforms and differentiates itself by being capable of running programmable transactions, i.e., smart contracts on the system [52].

### 2.3.1 Consensus algorithms

Distributed consensus algorithms are used to keep the truly decentralized structure of the network.

The certain algorithm that is used to reach consensus among the network nodes, affects key parametric of that blockchain network such as scalability, transaction speed, security and even electricity consumption of the nodes. There are trade-offs between their certain advantage and disadvantages. Although there are variety of consensus algorithms, either of Proof-of-Work (PoW), Proof-of-Stake (PoS) or modified version of these two are generally in use of the majority of the blockchain applications. In general, every algorithm needs a way to generate blocks and accept the proposed block by network members, a process called *reaching consensus*. Using a PoW-based blockchain network, e.g., Bitcoin, is not very suitable, especially for energy applications, because of the computational power and energy consumption. On the other hand, Ethereum uses a hybrid version of PoW and PoS. However, it’s stated that the Ethereum platform is planning to use PoS or slightly modified version of it with the version of ETH 2.0 in a couple of years to reduce the energy and resource consumption [53].

### 2.3.2 Ethereum and virtual machine

Ethereum is an open-source project developed by many people around the world and not controlled or owned by any particular person. It is not solely for storing or transferring value as its most counterparts. The main aim is to make anyone capable of building or using decentralized applications that run on blockchain technology [53].

Ethereum Virtual Machine (EVM) is in the center of the platform as a runtime environment, as it's fundamentally a level of abstraction between the machine and executing code. EVM helps development and portability of the code because it is an exquisite sandbox, a testing environment for those trying to create a smart contract without affecting the main blockchain operations. The remainder of the main network is fully isolated from an EVM instance. In the network, any Ethereum node can execute the same commands on their own EVM that provides code portability.

Speaking of resources, in EVM, there is a fee named 'gas' for computational cost of running certain piece of opcode on the network in order to prevent the denial of services attacks and increase the efficiency of the system.

Users can participate in the public Ethereum network and pay 'gas' to miner nodes, or a new private network can be created with permissioned miner/user nodes. In a public network, there is transparency, and the performance of the system is depended on the execution of the global network. On the other hand, in a private network, there is an initial ICT cost for servers and network, and a maintenance cost as well to have enough miner nodes, and it can cause centrality to certain degrees when more substantial nodes take the lead. In these networks, there are several factors, i.e., consensus algorithm, delay, number of nodes needed to be measured to show the performance. There are also semi-structured Ethereum networks, e.g., consortium blockchain that binds public and private networks on the same platform. There are pros/cons for public and private blockchain networks where the consortium blockchain is placed in the middle of these two architectures. To run consortium blockchain, there is a group of privileged nodes takes the lead over other participants.

### 2.3.3 Understanding smart contract

Smart Contract concept was envisioned by Nick Szabo as a computer-aided set of rules that provides an agreement in a group of peers. Vending machines are illustrated as a forefather of the smart contracts as it is a 'contract with a bearer' [54]. Smart contracts today are able to work autonomously on the Ethereum-based blockchain platforms that allow executing immutable digital agreements. In these platforms, agreement protocol among the contractors is initially implemented with a script and deployed to the network. When a specific data or command occurs, the deployed smart contract is being triggered automatically on the blockchain network, and the actions in this digital contract are followed. Thus, the whole business is completed transparently without needing trusted central authorities.

Smart contracts can be considered as wallets in the cryptocurrency concept since they have an account address and balance akin to standard cryptocurrency accounts. Hence, all other participants can transfer value between their own accounts and the smart contract. The only difference is that the business workflow, the protocol between the parties, is programmatically coded inside the smart contract. A function call or a transaction triggers the smart contract execution if the business logic holds at that time. When a new smart contract is implemented, it must be deployed to the Ethereum network. This process and all other execution steps are done by the peer nodes in decentralized concept. Thus, while deploying a new contract, or executing one, the system charges a little fee to handle these processes, which is called *gas*.

Creating new applications on the Ethereum platform is relatively easy and suitable for many real-world scenarios. Smart contracts are robust to interventions from outside since they are deployed to a blockchain, and kept in blocks anonymously, yet all the transactions can be monitored and traced publicly. Smart contracts have a value (essentially, it is a balance in Ethereum), an address, state, and functions that can change the state during the operation and eventually emits output events. These events can be captured by the external web or mobile applications so that the *dApps* come to life. It is highly likely that *dApps* will embody the *Web 3.0* infrastructure in the near future [52].

## 2.4 Proposed Architecture of Blockchain Based P2P Energy Trading in VPP

The VPP architecture requires known participants and power lines during the trading process to guarantee power distribution among all known users. Thus, the blockchain based solutions cannot be truly decentralized because of the oracle problem, and it naturally has some limitations on participation. Instead of using consortium blockchain platforms, e.g., Hyperledger, Quorum, or modified private Ethereum network, the public Ethereum network is being set to make the whole process transparent and adaptable to various backbone architectures. Hence, the platform can run communication and power distribution processes on different rules or networks efficiently. In this work, the communication and agreement are moved on to the public Ethereum network, which gives the adaptability. Public network transparently decides a pair of participants to assure power transfer between them, and it occurs when users become a part of the physical network. With this structure, it is also possible to run inter-VPP energy trading while we are offering an example of intra-VPP distribution in this work.

Figure 2.1 shows the proposed VPP model consisting of twelve agents, including consumer/prosumer, a big scale energy storage system (ESS), a diesel generator, and a P2P Energy Trading Coordinator (P2P_ETC). The VPP is controlled by P2P_ETC and technical VPP, and it is also connected to the upper-level entity, named as Market Operator to enable P2P energy trading. P2P_ETC is responsible for financial issues, e.g., investment, optimized revenue for exchanged energy, economical paradigms with ancillary grid services and participates in auction mechanism. It relies on agents' information shown with dashed line in Figure 2.1. Technical VPP (TVPP), as the name suggests, handles technical issues relevant to controls at agent and VPP level. There are information and power flow between the agents as shown in dashed and solid line in Figure 2.1. In order to make energy trading efficient, a bidding system between the agents that runs on the blockchain network is built. The Ethereum platform and smart contracts for these purposes are utilized. Every agent has public and private key pair to have an address on the platform.

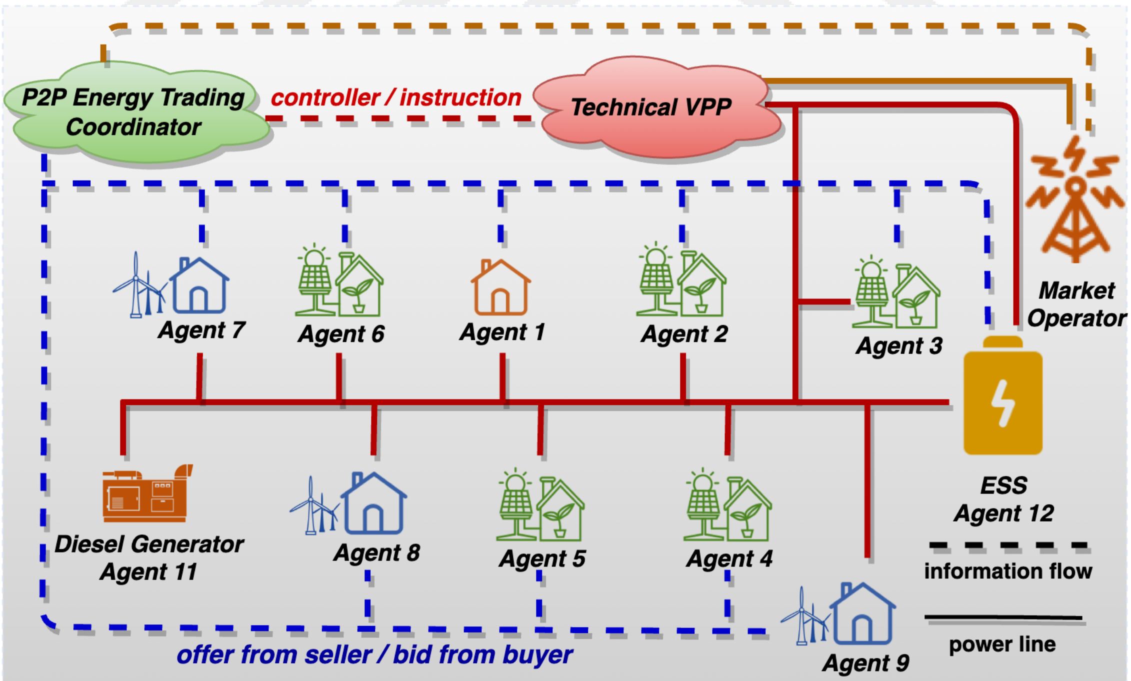


**Figure 2.1 VPP model architecture.**

In this proposed architecture, agents mostly have a prosumer role since they are able to produce energy from renewable sources, i.e., solar, wind when it is available. On the other hand, their role might be changing to a consumer in parallel when it is not available from the grid in accordance with VPP operation. When the agents have a surplus of energy, they will be able to sell those to other needful agents in VPP or connected VPPs. The seller agent will initiate the auction by deploying a smart contract, and buyers will bid for it to get the energy they require.

### 2.4.1 Smart contract implementation

Two smart contracts allow the system to handle a bidding mechanism between agents. The smart contracts are developed with the Solidity programming language and Remix browser IDE (integrated development environment). The stages of development and testing are summarized in Figure 2.2. The smart contracts are compiled by using solc.js over Remix Browser IDE [55]. By doing so, the bytecode and ABI (Application Binary Interface) of the smart contracts are generated. After this step, the bytecode can be deployed to the public or private blockchain test environments or real-time environment. A testing environment of Remix Browser's JavaScript VM, and Ethereum Ropsten Test Network is used [56].

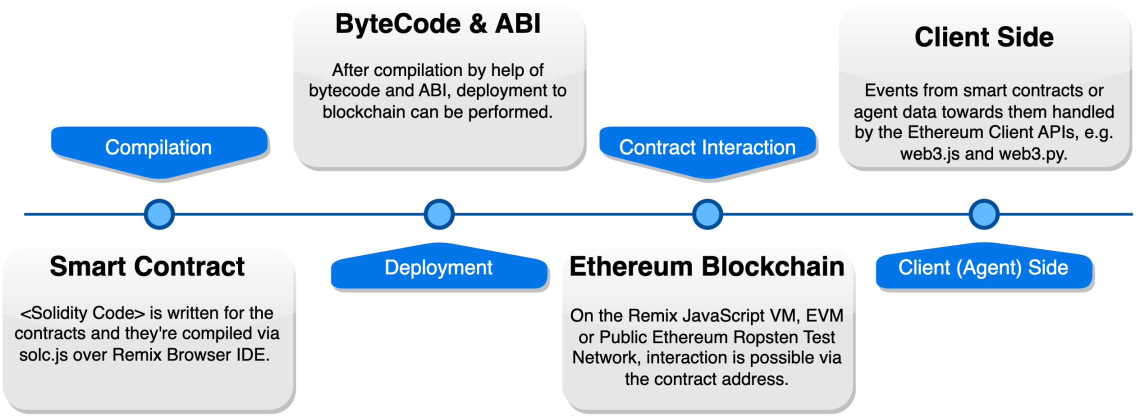


**Figure 2.2 Overview of proposed smart contract development and testing platform.**

Implemented *auction contract* has a straightforward interface, allowing agents to place bids and withdraw funds after the auction ends. In unexpected situations, the auction owner must be entitled to cancel the auction and to withdraw the winning bid. There has to be an *auction owner* to whom the winning bid will go when the auction finishes successfully. The auctions must have a start and end time. The block numbers can adjust this period since it is not safe to use block timestamps, which are set by miners and can be easily spoofed. Ethereum blocks are generated in approximately every 15 seconds, so the duration of auction can be calculated from these estimates instead of the easily modifiable timestamp fields of blocks.

In auctions, users try to bid the maximum amount that passes the highest bidder of the auction. Although there exist many different approaches for realizing the auctions in the literature, ‘open English Auction’ workflow is adopted in this study, giving the focus on smart contract implementation hurdles behind the approach to enable a successful P2P system within VPP framework [57], [58]. With the usage of smart contracts, it is needed to reduce the gas price for economic operation as well as increase the security, privacy, and transparency at the same time. According to the needs of VPP, this scheme seems the fair solution since other complex mechanisms can cause costly operations and code-security breaches of Solidity during Smart Contract implementation. Writing a smart contract is straightforward in terms of programming. On the other hand, avoiding logical, operational, and financial flaws in smart contracts that have complex mechanisms are difficult and significant. Due to this, ‘auditing smart contracts’ is becoming another special job description and requirement while developing distributed applications. Nevertheless, the proposed platform can be applied with different auction mechanisms with a small update as a modular design approach is followed in this study. Following are the essential key elements of the adopted auction:

- ***increment***: The bid increment amount which is set by the auction owner in the beginning.
- ***highestBidLevel***: Current highest bidding level, which will be the amount to pay when the auction finishes for the highest bidder.
- ***highestBid***: The highest bid that so far has been put in the auction.
- ***highestBidder***: The agent who made the highest bid until the current time.

When a new bid is greater than the previously highest one, the current highest bidding level is calculated as the previous top added to the bid increment amount. With this algorithm, the fairness of the competition is secured; otherwise, rich participating parties could overact easily to win all the auctions. Algorithm 1 summarizes the whole pipeline clearly.

**Algorithm 1**: Part of Auction Algorithm

```
Require: highestBid ≥ newBid > 0
newAmount ← newBid + increment
if newBid ≤ highestBid then
    highestBidLevel ← MIN(newAmount, highestBid)
else
    if msg.sender ≠ highestBidder then
        highestBidder ← msg.sender
        newHigh ← highestBid + increment
        highestBidLevel ← MIN(newBid, newHigh)
    end if
    highestBid ← newBid
end if
```

The auction smart contract works on top of four main modules. The user roles and implementation details for the public procedures are given as follows:

#### 2.4.1.1 Initialization/Construction module

This module controls certain preconditions, then sets some variables in the storage of the contract. For instance, during the creation of a new auction, the start time and end time must be proper. The start time must be before the end time, and end block number must be bigger than the current block number. Whenever agents want to initialize an auction, they have to deploy the auction contract with constructor parameters. Auctions must have an *owner* for each deployed contract; otherwise, it would not be possible to withdraw the funds. According to the running schemes, the P2P_ETC can be the only agent to have the ability to start a new bidding period, or each agent can deploy their own auction with their parameters.

#### 2.4.1.2 Bidding module

Making a new bid is not acceptable before the starting time, and after ending time or when the auction is canceled. It is very critical to block off the auction owner from making bids to their auctions. The owner can increase the price and manipulate the bidding to earn more. When a new auction starts, any agent can attend the bidding if there is no restriction rule made by the P2P_ETC. In Solidity programming language, the programmer can impose these restrictions by using reusable function modifiers. Making modifiers as simple and straightforward as possible they can be, helps to use them together in an efficient way. Users are able to send ETH (Ethereum) to make bids with this function. There may be cases that bidders need to withdraw their ETH:

- if someone makes a bid more than the highest bid.
- if someone makes a bid more than the highest bid level but less than the highest bid.

The smart contract does not automatically refund the funds; instead, the withdrawal module is used due to the security considerations. The smart contract sends ETH to a user when they explicitly request a withdrawal after all this bidding period is end [59].

#### 2.4.1.3 Withdrawal module

Upon completion of an auction, canceled or not, bidders should hold the ability to take their money (ETH) back. Only the auction participants can use this module for a withdrawing process. The cases that have to be handled by the smart contract for the requests are given as follows:

- the owner who opened the auction should be able to withdraw the ETH amount of the highest bid level since that is the award of the winner.
- the highest bidder should be able to withdraw their excessive part, which is the maximum bid minus highest bid level.
- excluding these two cases and users, any amount of ETH that sent to the smart contract should be able to withdrawn.

#### 2.4.1.4 Control module

When the system detects any fraudulent activities from the agents or the system itself, somehow, it cancels the whole pipeline automatically. It is implemented with the help of assorted modifiers in a smart contract. For instance, a canceled flag is changed to true under certain conditions such as '*only before end*' and '*by only owner*'.

In contrast to other programming contexts, writing Solidity contracts usually necessitates fewer lines of code, but attention to a great deal of detail. Until there are better tools to analyze security, gas, and readability considerations, which are very vital, developers will carry entire burden on their shoulders.

### 2.4.2 Execution

Once the smart contracts have been implemented, to use or invoke them, they should have been deployed into the Ethereum platform. In our proposition, they are being developed, tested, and deployed on to the JavaScript EVM of the Remix. The ABI or bytecode of the contract can be obtained from the compilation plug-in part of the Remix IDE. Afterward, in order to reach a real-time simulation of the implementation, they have been deployed to the Ropsten, which is a public Ethereum Blockchain test network.

In Figure 3.3, a sample execution of the contract is shown. First, three Ethereum test accounts had been created in Metamask, and their balance filled from some faucets. Faucets are third-party websites that are used to get some ethers (ETH) directly to related test network account address for testing purposes. Then the contract is deployed to Ropsten by using Metamask, which is a Web3 injection extension for the browsers and Remix. For contract creation 1520051 *gas unit* was used, and the gas price is in gwei ($1/10^9$ Ether), so it makes 0.001520051 Ether for deployment cost which converts to \$0.32 as of September 2019. Let us assume, Account1 is the owner of the contract and deployed it with the arguments as, *bidIncrement*: 75, *startBlock*: 1 and *endBlock*: 100000. In respective order, Account2 bids 40 wei ($1/10^{18}$ Ether), Account3 bids 1 gwei, uses a not payable method without sending any value. In respective order, Account2 bids 40 wei ($1/10^{18}$ Ether), Account3 bids 1 gwei, uses a not payable method without sending any value. As it is summarized in Table 2.1, this time Account2 bids 1 gwei, and its total bid becomes 1gwei + 40 wei. After that, Account3 bids 100 wei to win the auction. In the end, the highest bid becomes 1000000100 wei, Account3 becomes the highest bidder, and the smart contracts balance becomes 0.00000000200000014 Ether. Since a big interval for start and end blocks was set, the auction continues for a quite long time. It should be remembered that the accounts (agents) have to withdraw their related balances from the smart contract once the auction ends or canceled by the owner.

In a public blockchain network environment, it is possible to verify and publish the contract source code. Verification of source code and uploading it to the system gives extra transparency for all. Like normal agreements, a smart contract should provide more data to both parties regarding what they are *digitally opting* for and offer them the chance to audit the code independently to confirm that they are genuinely doing what they are meant to do.

**Table 2.1 Transactions and gas costs.**

| From | To | Event | Fee (Gwei) |
|---|---|---|---|
| *0x09d74e4a59a302...* | 0x0a44c9a35f9fe28... | Account1 deployed the contract, *bidIncrement*:75 | 0.001520051 |
| 0xd64bc9d9ef456c... | 0x0a44c9a35f9fe28... | Account2 bids 0.00000004 Gwei | 0.000087221 |
| 0x96dbf4ff6a2db8f... | 0x0a44c9a35f9fe28... | Account3 bids 1 Gwei | 0.000057211 |
| 0xd64bc9d9ef456c... | 0x0a44c9a35f9fe28... | Account2 bids 1 Gwei and its total bids and highest bid become 1.000000040 Gwei | 0.000042221 |
| 0x96dbf4ff6a2db8f... | 0x0a44c9a35f9fe28... | Account3 bids 0.0000001 Gwei, becomes highest bidder and winner | 0.000042221 |

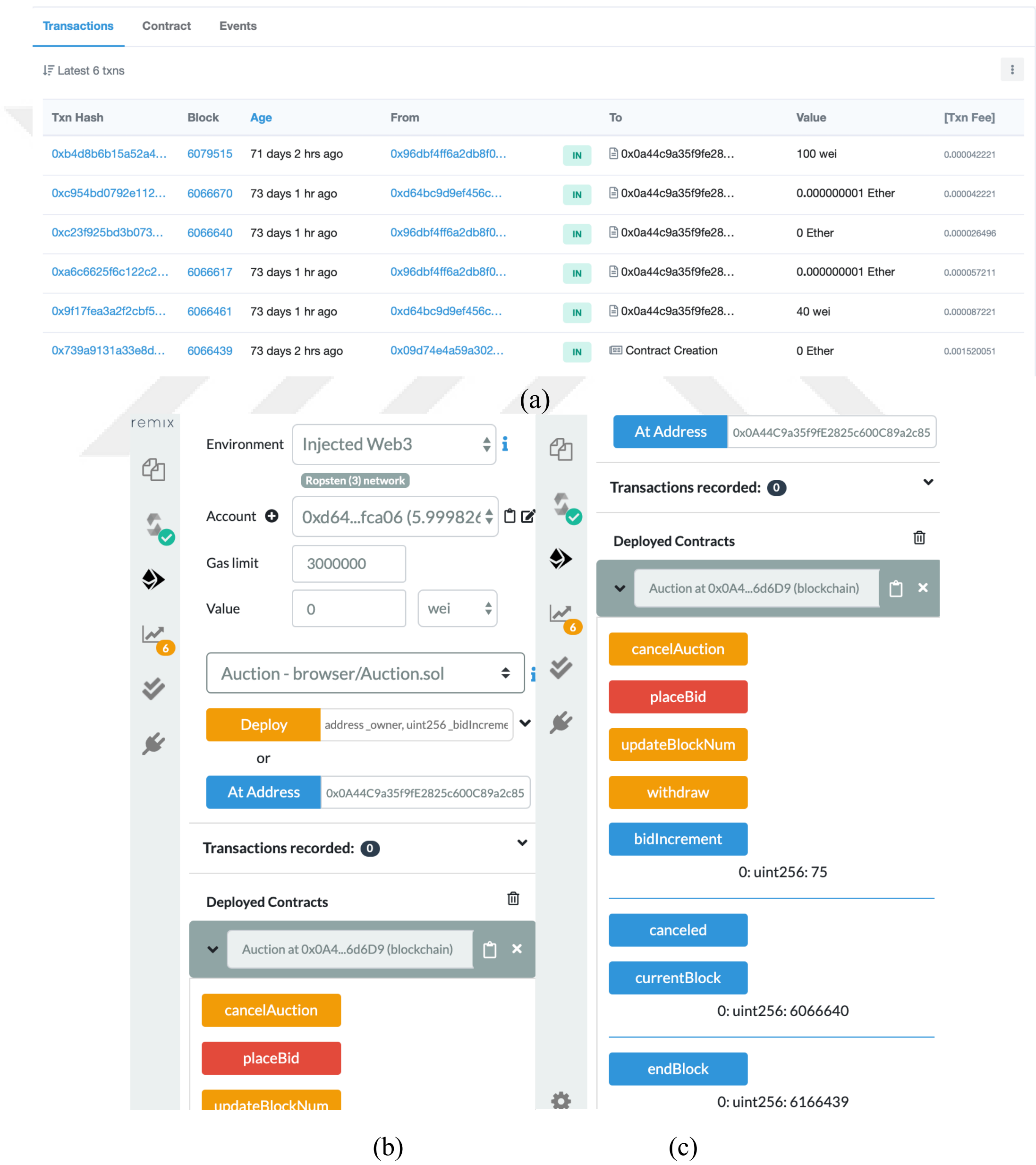


**Figure 2.3 Proposed smart contract in Remix. (a) executed transactions in Ropsten Test Network, (b) deployment, and (c) running.**

### 2.4.3 Running schemes

The proposed smart contract-based bidding platform can be adapted to different running schemes. In the given general scenario shown in Figure 2.4, once an agent has excessive energy to offer, it will inform the CVVP. After that, there could be three approaches to start a new auction:

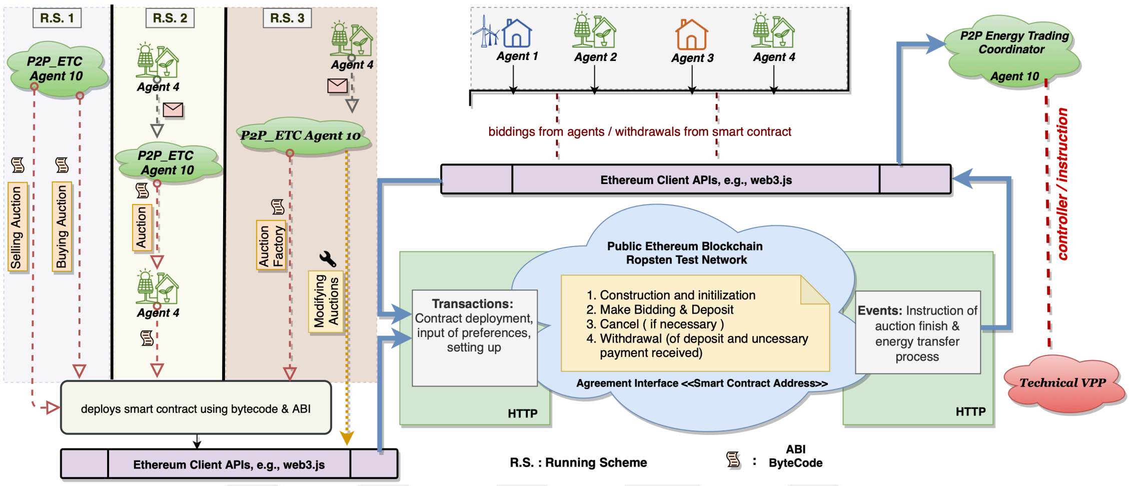


**Figure 2.4 Running schemes, flow and model architecture used in the proposed P2P energy trading.**

#### 2.4.3.1 Centralized approach - P2P_ETC deploys

P2P_ETC itself deploys the smart contract periodically for definite durations for buying or selling windows. This approach may cause the centralization problem, which contradicts the blockchain and P2P phenomena. P2P_ETC checks its database and energy profile in order to decide when the RES generate more energy, and there is excessive energy available for P2P trading within the VPP. Accordingly, P2P_ETC starts the auction by deploying the smart contract periodically for each auction. For example, around noon, when there is enough daylight to generate energy, P2P_ETC can have 20-minute-long buying auctions for every hour to collect energy from the producers. After that, in the rush hour, P2P_ETC starts selling auctions for the consumers, again with 20-minute-long periods.

#### 2.4.3.2 Secure approach - agent deploys

Agent itself deploys the smart contract, which could be safer but costly due to the initialization process. In this scenario, an agent, e.g., Agent 4, checks its smart meter and the system. Once the agent has excessive energy to sell others, informs P2P_ETC for starting a new auction. Using its database and current energy profile does P2P_ETC make the decision to let the agent start this bidding period. When P2P_ETC approves the request, the agent deploys the smart contract using its bytecode and ABI, which is already given the agents. The auxiliary software or operators of agents interact with smart contracts, i.e., deployment, setting parameters, or input of preferences with Ethereum Client APIs, e.g., *web3.js*, *web3.py*. Transactions towards Ethereum platform and events from there, are transferred over the network via HTTP (Hyper Transfer Protocol). When the auction is deployed, other agents who want to join the auction can make a bid to join the process in certain conditions, which is explained in section 2.4.1.

#### 2.4.3.3 Economy approach – P2P_ETC adjusts parameters

P2P_ETC deploys the smart contract factory that generates smart contracts on behalf of the agents. Here the smart contract named *Auction Factory* is used to create auction smart contracts to reduce initial costs. When a new auction request is submitted, P2P_ETC will adjust the parameters for the smart contract which is already deployed. With this approach, it is possible to avoid the deployment gas cost, but it may cause security risks due to the transparent background of the blockchain network. The whole communication among the agents and the P2P_ETC is made over the system via HTTP (Hyper Transfer Protocol). The proposed platform can run all these running schemes. P2P_ETC will decide to operate one of these schemes, according to worthwhileness to the system overall, i.e., cost or security.

### 2.4.4 Security discussion

In some other peer to peer energy trading applications, like vehicle-to-vehicle (V2V) or vehicle-to-grid (V2G) networks, privacy is very crucial since previously unknown EVs can come to charging stations to participate in the auctions [34], [42], [60]. At this point, the privacy brought by a private blockchain and sealing bids in auctions becomes important as well. However, in a VPP environment, there is no need for strict privacy or security measures like those platforms that have random participants. In the proposed framework participating agents are already known by the P2P_ETC and TVPP because of the backbone architecture. TVPP and P2P_ETC are in charge of all power transactions and financial transfer operations. Please note that, if the system has a potential random participant, in that case, the TVPP cannot assure to transfer energy to those nodes since they are not a part of the physical network. Bids made by the agents, cannot be tracked easily in a huge, real decentralized public Ethereum network in which also Ether cryptocurrency transfers are conducted. Ether is also widely used outside of the energy sector; therefore, agents can use it outside of P2P trading and directly reimburse, and unlike permissioned or private blockchain, TVPP and P2P_ETC will not be able to misbehave the tender because they will not be authorities that have privileges on the blockchain network [61]. As can be seen very clearly from the current literature, there is a trade-off between public blockchain and private blockchain usage. Namely, privacy protection for certain applications is a problem when using a public blockchain, whereas keeping accountability and transparency for the transactions is the problem when using a private blockchain. Using cryptographic methods to overcome the privacy protection problem in public blockchains is a solution that increases cost and complexity. Yet, in private or consortium blockchains, [62], centrality can increase, and organizations, aggregators or selected set of nodes determine the consensus that becomes permissioned, which contradicts inherent features of a truly decentralized blockchain [39]. In addition, although this trade-off is mostly considered in the privacy area, it is very important that the structure of smart contracts is simple and do not have unnecessary functions in order to avoid cyber security vulnerabilities and financial frauds previously seen in these networks [63]. Therefore, in a hybrid manner both two is used to balance this trade-off and outcomes are discussed as well.

On the other hand, by all means proposed framework inherently bears the security precautions and features that are coming to life by virtue of blockchain such as preventing double-spending, keeping transactions in a secure immutable common ledger, authenticating transactions and being in a true P2P manner.

#### 2.4.4.1 Random participants can attend the auction

It is not a meaningful attempt for the random participant unless it tries to do DoS attack. This problem is solved by selecting the next highest bid as a winner when the winner is not in the physical network. In that case, the fake winner cannot withdraw the bid back and that keeps the system secure.

#### 2.4.4.2 Participants can see others' bids and decide their strategy

It is assumed that all the participants are honest to reduce the cost of running the smart contract. In this article, the blockchain model is proposed and each module is abstracted to make the platform modifiable easily. When the network is heterogeneous and privacy issue becomes important, the auction module could be supported with cryptographic applications like sealed auctions, or encrypted comparisons to find the highest bid as in [64]–[66]. In that case, the gas price will increase but the system can deal with the privacy issue. Otherwise, as previously mentioned, a hybrid model akin to [62] can be adapted easily by using private blockchain for privacy-driven portions and public blockchain for transparency-driven portions of the proposed platform.

#### 2.4.4.3 General security concerns are solved by blockchain platform

Nobody can bid on behalf of some other nodes, it is not allowed to have double-spending, transactions are kept in a secure distributed database, and smart contract assures the trusted agreements between peers.

#### 2.4.4.4 Participants can apply different characteristics to get the advantage over others and that can cause some deadlocks

This issue is not about the platform itself, however, the proposed system can apply different penalty schemes on their VPP network. Please note that the proposed architecture is aimed to support VPP network with its peer-to-peer background. Different characteristics of participants will be analyzed as future work with game-theoretical approaches.

## 2.5 Case Studies

The proposed architecture is tested and validated under four different case studies by using a one-day realistic energy data from Australia, Perth Region. Figure 2.5 represents the total generation and the total load changes on a specific day. In this figure, the green curve represents the total load, and total production is represented with the orange curve. Also, the yellow curve shows the gap between the total production and total load at a specific time, and the blue curve is the ESS-aided version of the yellow curve in the VPP in 24 hours.

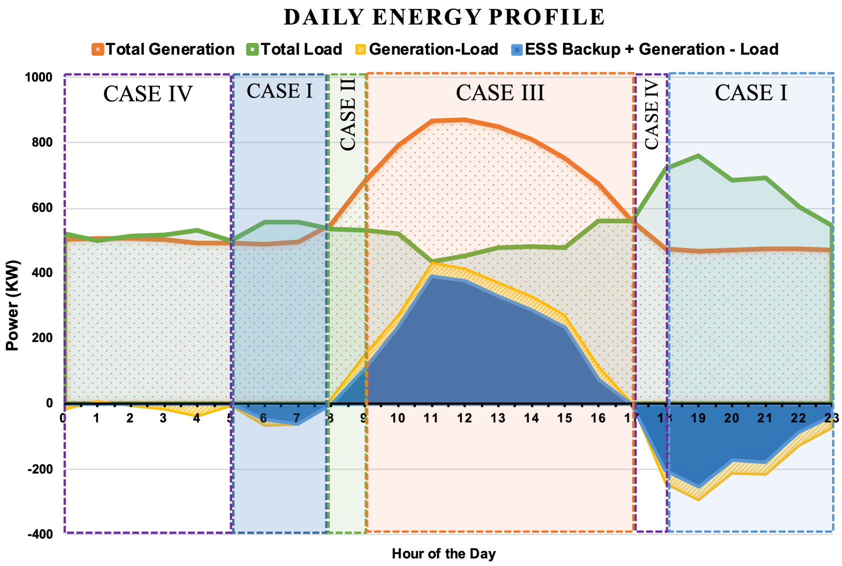


**Figure 2.5 Energy profile of the VPP (using realistic data).**

Based on the information given in Figure 2.5, it is observed that there could be four different cases that may occur during a day, as shown. In general, there could be two scenarios without ESS: (i) total generation could match with total load, or (ii) VPP needs to feed the system, e.g., trading with market operator, since the load is higher than the production rate. Please note that diesel generator and ESS are also considered as agents in the system. Therefore, they are able to buy/sell energy among all others in the proposed architecture. Thus, it is also needed to add two more cases to determine the roles of the ESS in these two general cases. Table 2.2 presents a general overview of the case studies whether the one-hour backup of ESS is sufficient, the energy demand in VPP is met or not, and the ESS is in charging or discharging status.

**Table 2.2 Overview of cases.**

| Cases | ESS Status | Satisfying Demand | Charging Status |
|---|---|---|---|
| I | short | not enough | discharging |
| II | short | just enough | charging needed |
| III | charged | enough | charging |
| IV | charged | just enough | discharging |

## 2.5.1 Case I

When ESS is short, and the total production is not enough to feed the demand, VPP needs to buy the power from the grid. These hours are represented as *Case I* in Figure 2.5. During these hours, there is definitely not enough energy in the system; however, smart contract must be still active in letting agents get energy from the producers. Since the agents are already out of power, it is better to use RS 3 to avoid the cost of deploying smart contracts. In Table 2.3 line four, the difference between Total Generation (TG) together with one hour backup of ESS and Total Load (TL) is drastically low that represents the Case I clearly and VPP cannot run the system without the help of market operator. Even though total energy is not enough in the VPP, there may be agents exceeded or failed behind their forecasted production. In a penalty condition, peers can trade with each other with the proposed platform. For this specific situation, the system could also allow running RS 2, which gives truly P2P trading among the prosumers in need not to get punished.

**Table 2.3 Cases during the certain time of the day.**

| Time | TG (KW) | TL (KW) | TG + Backup - TL | TG - TL | Cases |
|---|---|---|---|---|---|
| 03:00 | 502.9069 | 518.8 | 0 | -15.8930 | IV |
| 08:00 | 551.3342 | 536.4 | 0 | 14.9342 | II |
| 13:00 | 850.8720 | 479.0 | 331.8720 | 371.8720 | III |
| 21:00 | 476.1627 | 694.6 | -178.4372 | -218.4372 | I |

### 2.5.2 Case II

When the total generation is enough to feed the demand, but there is not enough energy in the ESS, the system should also charge the ESS since all of them are in charging mode. *Case II* is represented in Figure 2.5, when the yellow part is above zero between 8-9 am. In these hours, the number of trading and transactions occur on the blockchain architecture is increasing. In Table 2.3 at 8:00, the TG can match the TL but ESS cannot sell energy since they need to be charged. In this case, all three schemes are possible, but the first looks centralized, the third one is less secure, and so RS 2 is better to operate.

### 2.5.3 Case III

The difference between the Case II and Case III is the role of the ESS. In this case, ESS is probably in charging mode, yet they can sell energy as well. During this period, VPP is in islanded mode, and all trading and transactions are handled inside VPP. Thus, VPP could go to offline mode and let all peers manage themselves with the power of the blockchain architecture that eliminates third parties. In Table 2.3 line three, excessive energy is shown to explain that VPP can work in islanded mode with no doubt. It is recommended to operate RS 2 to be able to trade in a P2P manner and to reduce the communication cost that could happen when RS 3 is used.

### 2.5.4 Case IV

This is almost the same as Case I, but the role of the ESS is different. The difference between TG and TL is not as low as in Case I and more precisely, at 03:00 the difference between TG with ESS backup and TL is zero in Table 2.3. ESS has just enough backup to compensate the difference, which means it's in discharging mode. Others need to trade the energy from the ESS, otherwise VPP should feed the system with the help of market operator. Although there is no need to buy energy from the grid, VPP and market operator is still connected, where the blue line touches zero, from midnight to 5 am and at 5 pm. For this scenario, all three RS can work, but it is offered to operate RS 3 since there are a few participants interested in selling energy. P2P_ETC can deploy a contract and modify it when a new one wants to start an auction to avoid the cost of deployment.

### 2.5.5 Analysis

Proper running schemes for the given cases are discussed in this section. A high-level summarized overview and comparisons of running schemes for each case is given in Table 2.4. The proposed architecture requires P2P_ETC to open repeatedly buying and selling auctions, Running Scheme (RS) 1, for definite time periods regardless of the case to assure connectivity among all the participants. Other schemes can be applied based on the VPP power distribution conditions. There are two important factors while deciding the running schemes: (i) overall demand on the network, and (ii) ESS condition. When there is excess energy, in Case II and Case III, number of auctions will be increased for trading processes. Thus, RS 2 is recommended for both cases, especially for Case III it is strongly recommended to reduce the communication cost and assure truly P2P network. On the other cases, RS 2 is not recommended unless the penalty is not applied for unsuccessful peers that promise to generate a particular amount of energy in Case I. RS 3 is recommended when generated energy is not enough to run the network. Optional schemes can be chosen depending on the requirements and operational conditions.

**Table 2.4 Recommended running schemes.**

| | **RS 1** | **RS 2** | **RS 3** |
|---|---|---|---|
| Case I | Recommended | To reduce penalties | Recommended |
| Case II | Optional | Recommended | Optional |
| Case III | Optional | Strongly recommended | Optional |
| Case IV | Optional | Not recommended | Recommended |

## 2.6 Performance Evaluation

Blockchain-based solutions become hugely influential recently because of its transparent and distributed architecture. Since the technology is quite new, there are different evaluation metrics to measure the proposed system's performance. Each proposed platform can have distinct advantages over other solutions based on these metrics. The overall performance can vary depending on the description of the problem and its aims. According to the used platform, e.g., permissioned blockchain (Hyperledger) with chain code implementation or public Ethereum network with a smart contract, the measured performance metrics can be remodeled.

In this work, smart contract enabled public Ethereum network is introduced, and average gas costs are discussed in Table 2.1. Some other metrics are recommended to measure the overall performance of the blockchain platforms [67]. Since the proposed system is working on the public Ethereum network, it is not required to test fundamental metrics for the core platform, like transactions per second (tps), which is well-known. Instead, the smart contract's performance on Average Execution Time for different loads and cases are presented in this section. The execution time shows the elapsed time between a transaction request time, $t_{tx_{input}}$, and its confirmation with state updating in the network, $t_{tx_{confir}}$. In order to obtain the elapsed time between a bidding request from an agent to the smart contract and its confirmation notification from the network to the agent, *web3.js* scripts that we coded were utilized by connecting to the network via 'Infura.io'. The average value is calculated by taking an average for all the requests in a given time span, from $t_i$ to $t_j$, as shown in Equation (2.1).

$$AET = \frac{\sum_i^j \left(t_{tx_{confir}} - t_{tx_{input}}\right)}{Count\left(tx \text{ in } \left(t_i, t_j\right)\right)} \tag{2.1}$$

The general performance of the platform is measured when 1, 5, 10, 15, 25, 50, and 100 participants are located in the system. Furthermore, to show the case performances, tests are applied at different times. In this framework, the bidding mechanism is proposed for the agreement on the P2P matching process. The system is working on asynchronous mode, and two participants might try to increase the highest bid at the same time, which can cause conflicts. Hence, some of the bidding attempts could be refused when the number of participants increases. In Figure 2.6, the average number of successful biddings are presented to show the robustness of the platform. When the system is overloaded with 100 agents, 73 percent of the requests are approved by the smart contract. Figure 2.7 shows the average execution time under different workloads. Average execution time is affected by the load, and increasing the number of agents raises the processing time. With this result, 50 seconds is recommended as a period between the following requests from the same participant, to keep the system consistent. The smart contract performance in different cases is also evaluated, without Case II since it is considered a transition period. The results are presented in Figure 2.8 for 100 agents which is an overloaded scenario. Since there are many transactions needed to be processed in Case III, the average execution time becomes higher than other cases.

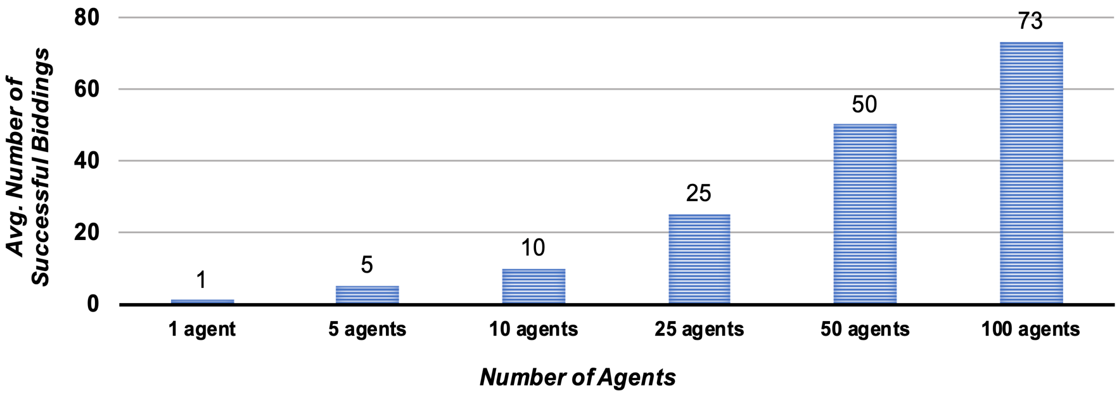


**Figure 2.6 The general performance of smart contract under different workloads.**

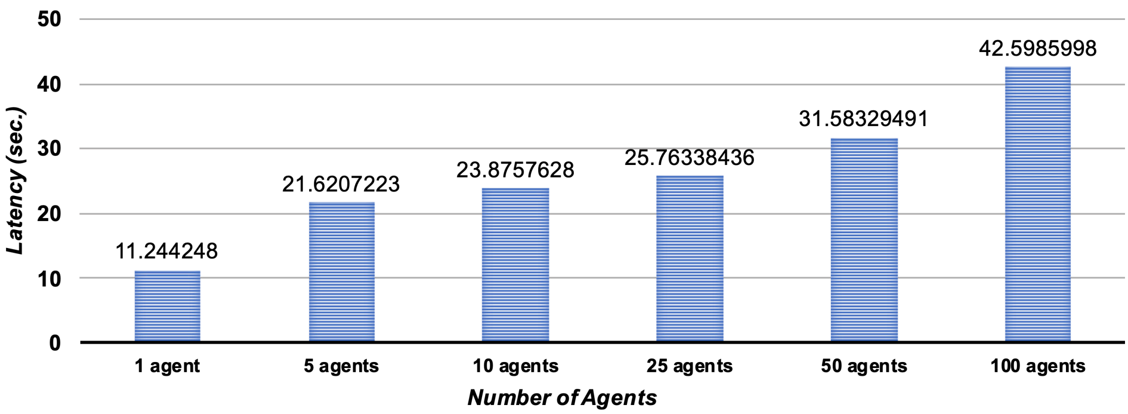


**Figure 2.7 Average processing time for bids when different number of agents use the system at the same time.**

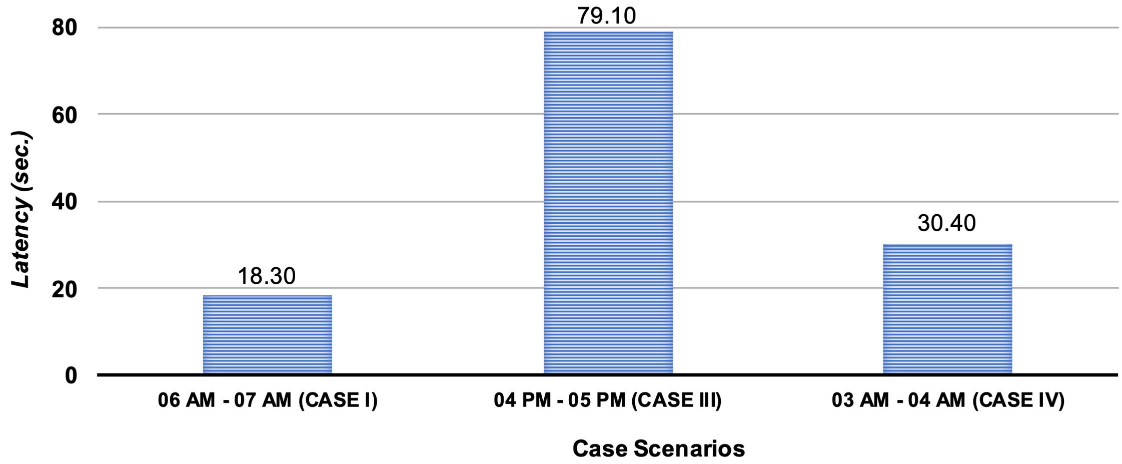


**Figure 2.8 Performance of the system under different case scenarios when it is overloaded with 100 agents.**

## 2.7 Conclusion

In this work, a blockchain-based bidding platform and cryptographic testing environment have been developed to achieve an efficient, transparent, and economic P2P energy trading within VPP framework using Smart Contract. A public blockchain, unlikely to other applications, is implemented, algorithmic steps are generated, and the usage schemes are discussed in detail. Smart contract development and implementation that facilitates P2P energy trading via auction-based bidding mechanisms are explained including the details of the functions. The proposed auction-based bidding platform interlinks various software, e.g., Solidity, Remix, Metamask, Infuro.io and Ropsten to enable blockchain-based energy trading which works in a real-life cryptographic environment. Possible running schemes are discussed to achieve effective bidding platform to deal with both cost and security concerns. In light of real generation load data from Western Australia, the suitable running scheme(s) for P2P energy trading under the developed platform is demonstrated and suitable recommendations are made.

In order to reach an optimized and efficient operation of the model(s), deep learning and artificial intelligence algorithms may be utilized. Auto-managing tools with deep learning, game-theoretical analysis for profit maximization of VPP, and other security and defense mechanisms are considered as the future tasks before commercializing the developed energy trading platform.

# Chapter 3

# Energy Trading on a Peer-to-Peer Basis between Virtual Power Plants Using Decentralized Finance Instruments

Over time, distribution systems have begun to include increased distributed energy resources (DERs) due to the advancement of auxiliary power electronics, information, and communication technologies (ICT), and cost reductions. Electric vehicles (EVs) will undoubtedly join the energy community alongside DERs, and energy transfers from vehicles to grids and vice versa will become more extensive in the future. Virtual power plants (VPPs) will also play a key role in integrating these systems and participating in wholesale markets. Energy trading on a peer-to-peer (P2P) basis is a promising business model for transactive energy that aids in balancing local supply and demand. Moreover, a market scheme between VPPs can help DER owners make more profit while reducing renewable energy waste. For this purpose, an inter-VPP P2P trading scheme is proposed. The scheme utilizes cutting-edge technologies of the Avalanche blockchain platform, developed from scratch with decentralized finance (DeFi), decentralized applications (DApps), and Web3 workflows in mind. Avalanche is more scalable and has faster transaction finality than its layer-1 predecessors. It provides interoperability abilities among other common blockchain networks, facilitating inter-VPP P2P trading between different blockchain-based VPPs. The merits of DeFi contribute significantly to the workflow in this type of energy trading scenario, as the price mechanism can be determined using open market-like instruments. A detailed case study was used to examine the effectiveness of the proposed scheme and flow, and important conclusions were drawn.

## 3.1 Introduction

Owing to the rising global demand for energy, growing political pressure, and public awareness regarding reducing carbon emissions, incorporating large-scale renewable energy sources (RESs) integration and contouring power system operation with information and communication technologies (ICT), modern electric power systems have been undergoing a revolution [68]. These concerns have led to the creation of the microgrid concept, which has seen significant developments and adjustments over the previous decade with the help of smart grid technology [69]. Despite the obvious benefits of microgrids, there are several technical obstacles, including stability and dependability issues, due to the inherent volatility and unpredictability of RESs [10]. Virtual aggregation methods, in which small-scale prosumers work together on a larger scale to acquire benefits that cannot be obtained on an individual basis, are now being implemented because of the legislative and economic constraints of the energy market. Virtual power plants (VPPs) come into play in that regard. They are theoretically utilized for DER consolidation such that they can serve as a completely dispatchable unit, processing data from a wide range of DER physical infrastructure, market operations, and distribution system operators (DSOs) [70], [71]. Moreover, VPPs can trade energy on behalf of small-scale DERs who cannot engage in the electricity market; therefore, VPPs can be considered an intermediary between DERs and the wholesale market. Inside VPPs, all the current ICT facilities are typically used to superintend the structure. Traditional cloud or fog computing systems are used to store the corresponding data necessary for VPP operations [11], [72].

Previously, electricity customers were connected to conventional central energy systems as only consumers. Nonetheless, this scenario has changed. In the new concept, customers are now called prosumers (combinations of producers and consumers) and can now generate electricity from DERs, the bulk of which are generally RESs [73]. Currently, excess energy is exported back to the grid based on net metering and Feed-in Tariff (FiT) billing schemes. A prosumer receives credit in kilowatt-hours for the amount of energy they export to the grid under net metering. The prosumer's electricity consumption, supplied by the main grid, is then deducted from the prosumer's credit. In the FiT scheme, the prosumer can export the surplus energy at a fixed price and receive a monetary credit rather than kilowatt-hours. However, these policies provide few benefits to prosumers and are being swiftly phased out in numerous countries worldwide.

Prosumers expect greater flexibility in allocating and managing their resources, as well as the elimination of intermediaries. The rise of prosumers necessitates a more decentralized and open energy market than the traditional, centralized market. Peer-to-peer (P2P) energy trading has emerged as an innovative paradigm at this juncture. P2P trading eliminates the need for third parties, allowing prosumers to exchange their surplus energy production with their peers directly. Since electricity generation with RESs is sporadic and unpredictable, the prosumers have to store excess energy in their ESS or sell it to the main grid, their peers inside the VPPs/microgrids, or neighboring VPPs (inter-VPP trading). However, a P2P trading platform is required to establish a marketplace for prosumers and consumers, providing them with flexibility and control over their generation and consumption. Furthermore, the platform must enable communication and exchange of information with peers, make agreements and transactions, and store this information in trustworthy databases. As the size of decentralized systems grows, so does the complexity of P2P trading [74]. Distributed ledger technology distinguishes itself from centralized servers and databases by enabling safe, decentralized communication and cooperation among peers. Distributed ledgers are databases that record transactions and other related data in multiple locations without the involvement of a central authority. Blockchain is one of the leading types of distributed ledger technology that offers unique features to support P2P trading by providing a high level of transparency, security, anti-tampering, and lower operational cost due to the elimination of mediators. Thus, the new blockchain-enabled P2P trading approach differs from the conventional, centralized method of trading electricity [12].

In the design of P2P energy trading, game theory methodologies [75]–[79], auction-based procedures [80]–[84], optimization methods [84]–[88], and blockchain-based technologies are commonly employed. In a competitive situation, game theory is applied when a player's decisions and behavior affect other players' results and vice versa. The paper in [75] proposed a non-cooperative game theoretic approach to optimize the social benefits of P2P energy trading in virtual microgrids. The Stackelberg game was used to minimize consumer costs and maximize producer profit. P2P energy trading was realized using a multi-objective game-theoretic optimization in [76], [77] for a clustered microgrid with three microgrids. The Nash equilibrium of game theory in these papers was used to determine the best number of participants and payoffs for peer-to-peer (P2P) and peer-to-grid (P2G) energy trading. Auction-based mechanism in energy, a significant subfield of game theory, can be thought of as competitive bidding processes among prosumers and consumers. An auction-based energy trading among peers is discussed in [80]–[82]. The double auction approach, which is one of the most widely used auction methods, has been applied in [82], [83]. It facilitates the involvement of market participants who play a role in regulating the market price to optimize the trading strategy. A double auction-based energy trading system for smart energy communities was proposed in [84]. This paper dynamically handled the price of energy trading by integrating Lyapunov-based energy control. Optimization-based methods were also studied for the efficient realization of P2P energy trade among VPPs or microgrids [70], [84]–[88]. The optimization techniques in P2P energy trading have primarily aimed to maximize the financial benefits of participants. The study in [87] demonstrates the P2P energy trading among microgrid clusters and the shared energy storage system. Improvements in energy use efficiency and cost savings were achieved by optimizing the proposed structure. Authors in [88] present an equilibrium model of a P2P transactive energy market. In this model, each member seeks the maximum personal advantage while having the option of importing or providing energy from/to other peers. The market equilibrium condition is represented as a MILP and solved using a commercial solver to internally calculate the energy transaction price. Nevertheless, most of the methods mentioned above have a substantial computational burden, especially as the number of interconnected VPPs increases. These implementations do not consider data and financial exchange platforms, decentralization of the energy trading system, and the elimination of intermediaries. To address these limitations, this study proposes a P2P trading scheme for a distributed network of VPPs using Decentralized Finance (DeFi) instruments.

Several survey articles can be found in the literature examining all aspects of the blockchain idea in P2P energy trading [73], [89]–[97] . Double auction variants stand out among the many financial approaches that can be categorized in the virtual layer of P2P energy trading designs [96]. Multiple vendors and buyers participate in a double auction to buy and sell energy. In order to match potential sellers' asks and buyers' bids with a clearing price, the intermediate market institution will receive submissions from both potential vendors and buyers [95], [97]. While using the blockchain to record energy trading transactions transparently and irreversibly, SCs take over the crucial role of these intermediaries [91]. Recent studies on P2P trading in the literature have mostly focused on local energy trading (intra-VPP/microgrid) utilizing blockchain and smart contracts (SCs). Our previous study also proposed an Ethereum-based intra-VPP P2P trading model with technical implementation details, analyzing the performance of public blockchain usage [6]. The state-of-the-art blockchain networks have the ability to run SCs, paving the way for the deployment of blockchain-based general applications. Ref. [98] is an elaborated report from a software engineering perspective regarding the SCs for transactive energy. A fully P2P energy trading market design for households has been provided by [99]. The study incorporates two trading approaches to analyze the impact of bilateral trading preferences. The first approach seeks to balance extra power and demand, while the second is intended to encourage energy trading among nearby peers. Ref. [100] presented two frameworks using Ethereum's SC functionality for a microgrid: a continuous double auction framework and a uniform price, double-sided auction framework. The paper's findings demonstrated that integrating the microgrid with P2P energy trading can strengthen the traditional centralized energy grid.

Some studies in the literature consider energy trading between VPPs as our study. The authors in [101] developed a hierarchical energy trading framework for both inter- and intra-VPPs. The MILP model was proposed to optimize the operation of the DERs in the system, considering the energy cost of each prosumer. A blockchain-based SC was used to record and automate transactions. Ref. [102] suggested a hybrid energy trading solution on a decentralized computer platform for microgrid clusters. This hybrid method combines linear programming with SCs on the Ethereum network. The other paper [103] proposed hierarchical energy trading between VPPs of small-scale prosumers using SCs. The optimization problem, which is to minimize the energy cost and meet energy service requirements, is addressed using a knapsack solution algorithm. However, the proposed solution was validated by a proof-of-concept prototype using Ethereum. Another authentic paper introduced a cryptocurrency-based energy trading platform (CETP) [104]. CETP uses the energy blockchain cryptocurrency (EBC) as a token for the electrical transaction between the stakeholders and performs the bidding indirectly through real-time bidding in EBC. This article aimed to improve the social welfare of the participants and inspired our work to be able to trade without the need to write SCs by ordinary system users. Nonetheless, CETP will probably not go from concept to practice since the designed trading system does not use an existing live blockchain environment. The proliferation of numerous VPPs and inter-VPP energy transfers seems likely, especially with the impending EV revolution. This possible inter-VPP trade requirement necessitates more efficient methods and flows by using more intensively the emerging tools and concepts of the blockchain ecosystem beyond the double auction approach in the financial layer. In order to perform a double auction in a blockchain-based solution, it is necessary for the agents or system operators to write a SC [105]. Failure to properly develop and audit SCs can also cause security and financial fraud problems, which have not been considered until now in transactive energy research, although many notorious incidents have happened in the blockchain world [106]–[109]. Therefore, in this study, a P2P trading scheme and framework between VPPs were developed by leveraging the benefits of the Avalanche ecosystem, such as speed, scalability, backward compatibility with the Ethereum network, and interoperability of Avalanche's C-chain together with multiple Ethereum Virtual Machine (EVM) based blockchain networks. Decentralized exchange (DEX) was used in the financial layer of our approach. To the best of our knowledge, our study proposes using DEXs for the first time in the financial layer of intercommunity P2P trading as a novel approach. Using DEXs to trade energy by tokenizing energy between VPPs can cut down on the use of SCs that are not written well and can be exploited. DEXs are run by SCs that have been developed and audited by professionals. They work in the public eye and handle much traffic. Experts in the field solve the problems they encounter in the live setting.

In contrast to the articles that were stated earlier, the purpose of our research is to investigate how DEX operations can be used to regulate the financial functioning and flow of P2P trading. Through tokenizing the energy of each VPP, supply and demand determine the parity balance between the tokens of VPPs. Therefore, trading in energy in the proposed scheme does not always require an auction or a bidding process. It also paves the way for trading operations like the open market without using order books.

The proposed scheme and flow are implemented based on the needs of the inter-VPP framework, using the Avalanche Platform (C-Chain, Fuji Test Network), Remix, and Pangolin, and the optimization model is formulated as mixed-integer linear programming (MILP), which is solved by the CPLEX solver included in GAMS. The contributions of this study can be summarized as follows:

- As an extremely novel approach for a blockchain-based P2P trading scheme, trading has been realized with a workflow close to the open market mechanism in this study, which is completely distinguished from papers that feature auction or bidding.
- It has been demonstrated that the trading on a model architecture is substantially realized; this scheme and workflow may be utilized in trading between VPPs. Further, energy prices can be calculated based on supply and demand.

- A workflow and schematic are presented where VPPs using different blockchains for trading can also trade with each other.
- While peer-to-peer trading is conducted on the model architecture of the power system comprising VPPs with the proposed flow, MILP is employed to get the cost of energy transfers closer to the optimum.

This study is structured into six sections. The Background Information section presents theoretical and conceptual details regarding the DeFi instruments. The System Description section describes the proposed methodology for the model architecture and problem formulation. The Proposed Scheme and Flow section details the inter-VPP trading platform's proposed scheme and flow. Finally, Discussion Section presents the analysis and results, while the last section provides the conclusions and future research avenues.

## 3.2 Background Information

Blockchain is the technology behind cryptocurrencies and digital P2P money transfers, which have become increasingly popular in recent decades. Fundamentally, it is a vast, widely distributed, and immutable digital ledger. As the name suggests, many blocks cryptographically interconnect to embody a chain of blocks that keeps the transactions intact. Multiple nodes scattered worldwide operate in a distributed fashion by consensus between them, removing central intermediaries and creating a massive registry and computing device. Blockchain is pushing for significant, transformative, and disruptive development in many sectors. The most promising future features of blockchain are decentralization, security, transparency, and fault tolerance. SCs are one of the benefits of blockchain, which makes a substantial difference in practical usage. They are predefined protocols between parties, programmatically coded, and live over the blockchain network autonomously. The usage of SCs in P2P energy trading is primarily for business logic flow and mandating market rules, that is, auctions and bidding mechanisms. Ethereum is an open source blockchain platform that aims to make anyone capable of building or using decentralized applications (DApps) that run on blockchain networks primarily by using SCs [110]. DApps are expected to become a new phase in the worldwide web's development process [111], [112].

Since its inception by [110], Ethereum has swiftly grown to become the world's second largest cryptocurrency, with the potential to challenge Bitcoin's dominance in the future. The initial coin offering (ICO) tsunami, which swept the globe in 2017, increased Ethereum usage by a factor of ten. Although the ICO excitement has died down, the rise of decentralized finance (DeFi) and non-fungible tokens (NFTs) have sparked a second wave of Ethereum adoption, as the majority of DeFi and NFT platforms are built on the Ethereum blockchain. However, scalability concerns, such as high gas prices, network congestion, and slow throughput are becoming more common in Ethereum-based applications. Layer 2 alternatives—which use new consensus protocols such as Proof-of-Stake and Byzantine Fault Tolerant to replace the energy-intensive and environmentally harmful Proof-of-Work protocols—have been developed to overcome the Ethereum scalability trilemma: Blockchains, such as Ethereum, are prone to the infamous trilemma, which states that it is impossible to accomplish decentralization, scalability, and security simultaneously. As they use the proof of work mechanism, both Bitcoin and Ethereum are extremely secure and decentralized, yet they have low transactions per second. The current solutions for this fall into one of the Layer 1 or 2 categories [113]. Layer 2 protocols are based on the Ethereum Mainnet, whereas Layer 1 protocols are all new types of blockchain. Layer 1 protocols are blockchain architectures not constructed on top of another blockchain [114]. The Avalanche blockchain, for example, is a Layer 1 blockchain system that has seemingly addressed the Ethereum trilemma using its own design and unique consensus mechanism. In contrast, Layer 2 is a protocol constructed on top of an extant blockchain. For example, Lightning Network is a Layer 2 solution for Bitcoin, whereas Loopring is a Layer 2 solution for Ethereum. The Ethereum 2.0 upgrades are another significant step forward in the attempt to increase Ethereum's scalability. Ethereum 2.0 is a series of Ethereum blockchain modifications that are presently under construction to make the network more scalable, secure, and durable [115]. However, these development efforts have been on the agenda since 2014, as applying these changes to an existing operational network with backward compatibility is difficult. Therefore, many Layer-1 blockchains have recently emerged as significant alternatives. Nevertheless, there are other protocols that are neither Layer 1 nor Layer 2 solutions but separate blockchains that operate alongside another Layer 1 blockchain. They are primarily a fork of the Ethereum blockchain rather than a Layer 1 or 2 protocol. For example, the Binance Smart Chain is a fork of the Ethereum blockchain rather than a Layer 1 or 2 protocol.

### 3.2.1 Avalanche platform

Avalanche is an open-source platform for deploying decentralized apps and business wide blockchain installations in a unified and highly scalable environment. Avalanche was the first decentralized SCs platform for global finance with near-instant transaction finality. Because Solidity works out-of-the-box, Ethereum developers can easily build atop Avalanche. The Snow family consensus protocols distinguish Avalanche from other decentralized networks. Generally, it is assumed that blockchains must be sluggish and non-scalable. To deliver strong safety guarantees, expedient finality, and high throughput without compromising decentralization, the Avalanche protocol adopts a revolutionary method for consensus and uses repeated subsampled voting. When a validator decides whether a transaction should be allowed, it polls a small, random group of validators for their opinions. If the queried validator believes that the transaction is invalid, has already rejected it, or prefers a different competing transaction, it will respond that the transaction should be rejected. Otherwise, the validator approves the transaction if a sufficiently significant share a (alpha) of the sampled validators respond that it should be accepted. That is, it will respond in the future when enquired about the transaction that it believes should be accepted. Similarly, if a sufficiently significant number of validators respond that the transaction should be refused, the validator will reject it. The validator repeats this sampling process until a of the validators questions the response in the same way (accept or reject) for b (beta) rounds in a row. When there are no issues in a transaction, it is typically completed quickly. When disputes occur, honest validators rapidly cluster around them, creating a positive feedback loop until all accurate validators prefer that transaction. Consequently, non-conflicting transactions are accepted, and conflicting transactions are rejected. If any honest validator approves or rejects a transaction, all honest validators accept or reject that transaction (with a high likelihood based on system settings) [116].

Avalanche features three built-in blockchains: an exchange chain (X-chain), a platform chain (P-chain), and a contract chain (C-chain). All three blockchains were validated and secured using the primary network, a particular subnet. Further, all members of all custom subnets must be members of the primary network by stacking at least 2000 AVAX (explained below).

#### 3.2.1.1 Principles

Avalanche is intended to establish permissioned (private) and permissionless (public) blockchains for application-specific usage as well as to develop and deploy highly scalable DApps and digital assets with different complexities and unique rules, commitments, and bindings (smart assets). Avalanche's overall goal was to provide a unified platform for creating, transferring, and digital trading assets.

#### 3.2.1.2 The native token: AVAX

AVAX is a native token of Avalanche. It is a hard-capped (720,000,000 tokens, with 360,000,000 tokens available on mainnet launch), scarce asset that is used to pay fees, secure the platform through staking, and provide a basic unit of account between the multiple subnets created on Avalanche. One nAVAX is equal to 0.000000001 AVAX. Unlike other capped-supply tokens that maintain a constant pace of minting, AVAX is meant to respond to changing economic situations. AVAX's monetary policy aims to strike a balance between users' incentives to stake the token versus utilizing it to interact with many services on the platform.

### 3.2.2 Decentralized finance (DeFi)

Decentralized Finance (DeFi) uses the same blockchain technology as cryptocurrencies. DeFi is a catch-all word for the cryptocurrency world dedicated to creating a new, internet-native financial system, with blockchains replacing existing mediators and trust mechanisms. DeFi gives end users the level of transparency, control, and accessibility they lack when dealing with centralized finance [117]. Intermediaries such as banks or stock exchanges are required in the traditional, centralized financial system to transmit or receive money. All parties must trust that intermediaries will behave fairly and honestly to have confidence in the transaction. These intermediaries were replaced by software in DeFi. People trade directly with one another instead of going via banks or stock exchanges, with blockchain-based 'smart contracts' (SCs) handling the job of creating markets, settling deals, and guaranteeing that the entire process is fair and trustworthy. DeFi also comprises loan platforms, prediction markets, options, and derivative markets, all of which operate on decentralized blockchain networks. DeFi instruments have already processed tens of billions of dollars worth of cryptocurrency, and this number is increasing daily [118]. SCs are not available on every blockchain platform. Users can write open-source, self-executing code on SC-supporting blockchain platforms to fuel more innovative, trustless transactions. Once SCs are deployed to the blockchain, their code cannot be modified anymore, and they continue to operate autonomously. These characteristics enable the development of a vast array of decentralized applications (DApps) on blockchain networks, with decentralized finance (DeFi) constituting a prominent subset.

### 3.2.3 Decentralized exchange (DEX)

A decentralized exchange is an excellent example of the growing suite of DeFi applications that allows two interested parties to conduct direct cryptocurrency trades, or more precisely, swaps. DEX was designed to address the shortcomings of centralized exchange (CEX). Trading cryptocurrencies has always necessitated the use of a centralized exchange (CEX). CEXs are administered by a firm or an individual with a profit motive. CEXs match cryptocurrency buyers and sellers in an order book, earn from the price spread between bids and asks, and commission per transaction. Therefore, they function similarly to traditional stock exchanges. However, DEXs are nothing but advanced DApps, which consist of professionally written and audited SCs in fact. In DEXs, the SCs that are deployed and living on the blockchain are doing most of the jobs, such as creating parity, managing parity liquidity pools, and swaps. They constructed P2P marketplaces directly on the blockchain, allowing traders to independently maintain and manage their assets. Users of such exchanges can conduct cryptocurrency transactions directly among themselves, without the need for a third party.

- **Pangolin**

  The Avalanche Platform's primary DEX is the Pangolin. It was introduced to the Avalanche network in February 2021 as a pre-tried idea for automated market makers (AMMs). In its first year, it enabled nearly $10 billion in trade activities. Pangolin can trade all tokens minted on the Avalanche and Ethereum platforms using the Avalanche Bridge (AB). Pangolin is a community-driven DEX, and its entire operation is executed by open-source and audited SCs [119].

## 3.3 System Description

### 3.3.1 Model architecture

Figure 3.1 illustrates the model architecture used in this study, which comprised three VPPs. These VPPs utilize either the Avalanche platform (AVAX-based VPP) or the Ethereum Platform (ETH-based VPP) for their intra-VPP trading operations. They trade their excess power among each other (inter-VPP) and the grid while taking their optimal costs into account. AB takes the stage alongside the Pangolin DEX when transacting between different blockchain-based VPPs, and only the Pangolin DEX is used when transacting between the same blockchain-based VPPs. AB is used to transfer ERC-20 tokens from Ethereum to Avalanche's C-chain and vice versa. Every VPP has its own specific token minted on the Avalanche C-chain. Try Energy Token (TRY) is the name of the token minted for this purpose. *TRY1*, *TRY2*, and *TRY3* are the tokens of the VPP1, VPP2, and VPP3, respectively. These are minted as per the ERC-20 Fungible Token standard using the SC from OpenZeppelin [120]. VPPs price the power they sell with their specific token, that is, $VPPi$ sells the power to $VPPj$ with $TRYi$ token, where $i, j \in \{1,2,3\}$ and $i \neq j$. They used Pangolin DEX for swapping tokens to get other VPP's tokens. The exchange rate/parity between them occurs in the Pangolin according to the supply/demand of the tokens in the liquidity pools. In fact, VPPs basically tokenize their energy. Thus, VPPs can reach optimum operation with minimum energy cost by trading with each other with the tokens.

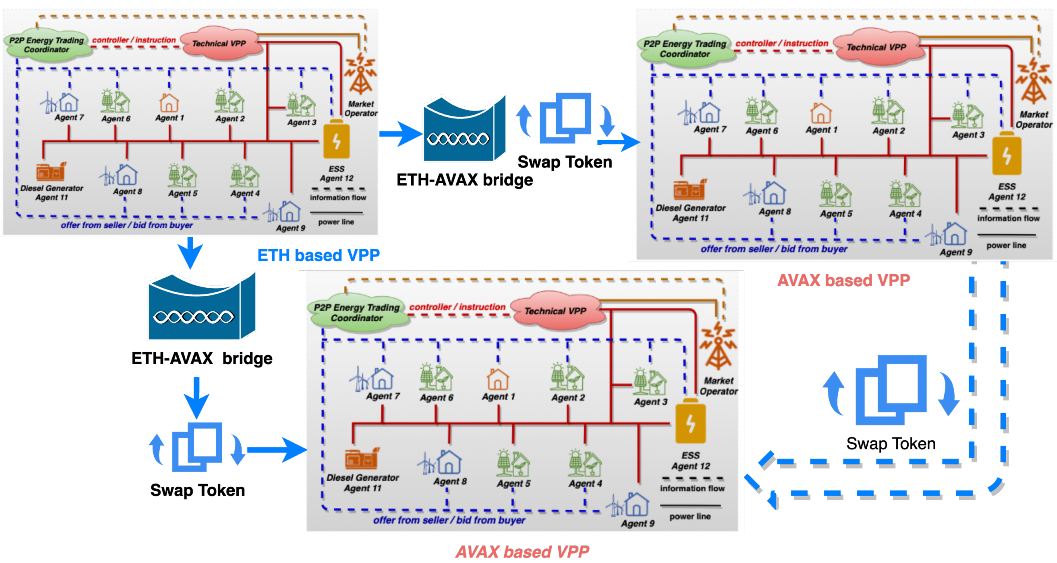


**Figure 3.1 Trading flow between different blockchain-based VPPs.**

### 3.3.2 Problem formulation

The objective function is to minimize the sum of the income and expenses associated with all bi-directional energy transfers to and from other VPPs and the grid during a given time horizon. When a VPP sells energy to other assets, it receives a profit as income. Cost is defined as an expense when it purchases energy from other assets. The objective function ($C_t$) is formulated as written in Equations (3.1) and (3.2).

$$objective\ function\ \min\{C_t\}, \tag{3.1}$$

$$C_t = \sum_i \left(P_{i,t}^{sold,grid} \cdot PR_t^{sold} - P_{i,t}^{purc,grid} \cdot PR_t^{purc}\right) + \sum_{i \neq j} \left(P_{i,t}^{sold,j} \cdot \gamma_{i,t} - P_{i,t}^{purc,j} \cdot \alpha_{j,t}\right), \tag{3.2}$$

where $i, j \in \{1,2,3\}$ and $t \in \{1,2,3, \dots, 24\}$ are the indices of VPPs and time, respectively. $P_{i,t}^{sold,grid}$ and $P_{i,t}^{purc,grid}$ represent the power sold to and purchased from the grid at time $t$ by $VPPi$, respectively. $P_{i,t}^{sold,j}$ and $P_{i,t}^{purc,j}$ denote the power sold to another $VPPj$ and that purchased from another VPP at time $t$, respectively. $PR_t^{sold}$, $PR_t^{purc}$, $\gamma_{i,t}$, and $\alpha_{j,t}$ indicate the power sell price to the grid, purchase price from the grid, *i*-th VPP's selling price to the *j*-th VPP and purchasing price of *j*-th VPP from *i*-th VPP at time *t*, respectively.

For the safe operation of the system, cooperative power balance should be taken into consideration as follows:

$$P_{i,t}^{sold} = \sum_{i \neq j} P_{i,t}^{sold,j} + P_{i,t}^{sold,grid}, \tag{3.3}$$

$$P_{i,t}^{purc} = \sum_{i \neq j} P_{i,t}^{purc,j} + P_{i,t}^{purc,grid}, \tag{3.4}$$

$$P_{i,t}^{T} = P_{i,t}^{sold} - P_{i,t}^{purc}, \tag{3.5}$$

$$P_{grid,t}^{T} = \sum_i P_{i,t}^{sold,grid} - P_{i,t}^{purc,grid}, \tag{3.6}$$

$$\sum_i P_{i,t}^{T} + P_{grid,t}^{T} = 0. \tag{3.7}$$

Equation (3.3) shows the total power sold by the *i*-th VPP, $P_{i,t}^{sold}$, to other VPPs and the grid at time *t*. Equation (3.4) indicates the total power purchased by the *i*-th VPP, $P_{i,t}^{purc}$, from other VPPs and the grid at time *t*. The total power exchange of each VPP,

$P_{i,t}^{T}$, and grid, $P_{grid,t}^{T}$, at time $t$ are given by Equations (3.5) and (3.6), respectively. The power balance equation of all system at time $t$ is formulated by Equation (3.7).

## 3.4 Proposed Scheme and Flow

The scheme and flow are close to the open market, unlike preliminary P2P energy trading studies in the literature. The literature review clearly shows that the energy price negotiation procedure used for P2P trading so far involves auctions or bidding mechanisms. Figure 3.1 shows a general perspective that illustrates the capabilities of this scheme. An ETH based VPP as in our previous study, can trade with an AVAX based VPP via an ETH-AVAX bridge, for example, AB. When AVAX based VPPs are trading among themselves, they only need to use a DEX, for example, Pangolin, to swap their tokens. It is known that there will be many different blockchain-based VPPs and microgrids operating around. The interoperability and trading ability of these among themselves will be more significant than they are now.

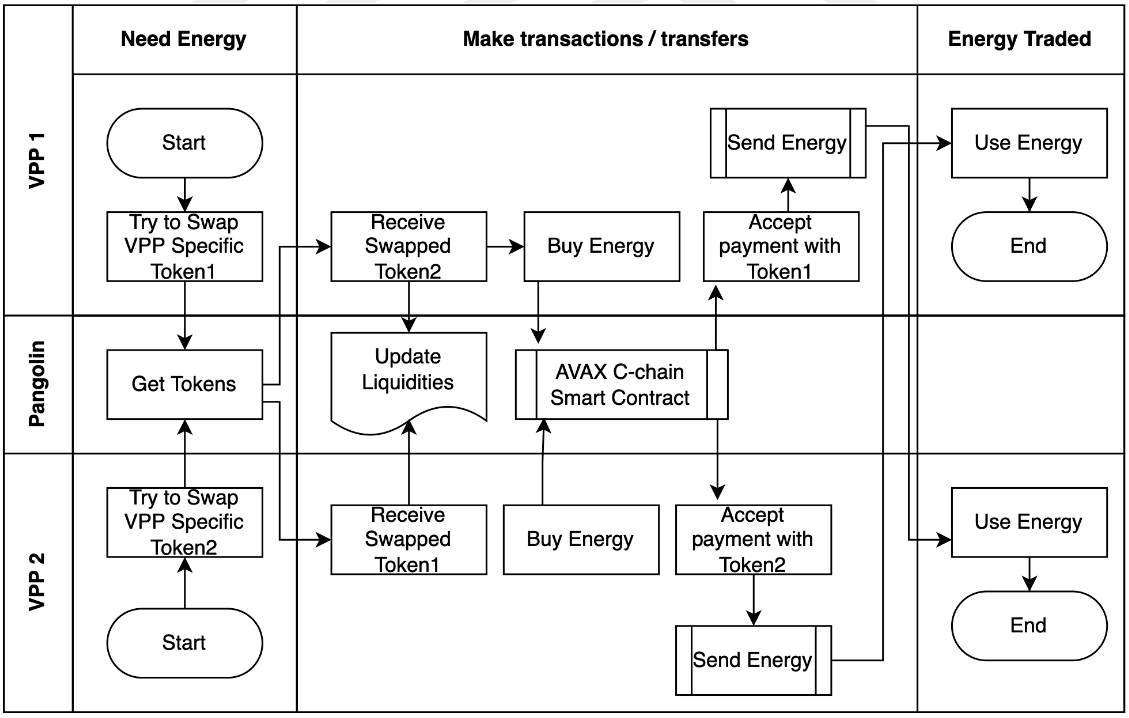


**Figure 3.2 Inter-VPP energy trading workflow.**

Figure 3.2 further details this flow. Regarding the energy transfer that occurs between VPP1 and VPP2, VPP1 goes to the Pangolin to swap TRY1 for TRY2 tokens with the exchange rate at that time. Subsequently, VPPs can choose to add liquidity to

Pangolin's liquidity pool, for example, TRY1/TRY2 if it would be beneficial for their own. They buy the required energy with swapped tokens from an SC that acts as custodian. Consequently, energy prices can be determined in a supply/demand manner. Note that payments are made using the counterpart's tokens.

# 3.5 Discussion

Figure 3.3 shows the daily power profile of each VPP. From this graph, one can observe that VPP1 has a power deficiency of 25 KW at the 1st hour, whereas at hour 9, it has an excess energy of 68 KW to sell to other VPPs and/or the grid. These excess/deficient states of power vary from hour to hour, and from VPP to VPP. The hourly electricity price given by the utility is presented in Figure 3.4. The time of use (ToU) electricity tariff of \$0.21, \$0.27, and \$0.42 is considered in this study. However, the electricity tariff is flat for power injected/sold to the grid, \$0.1.

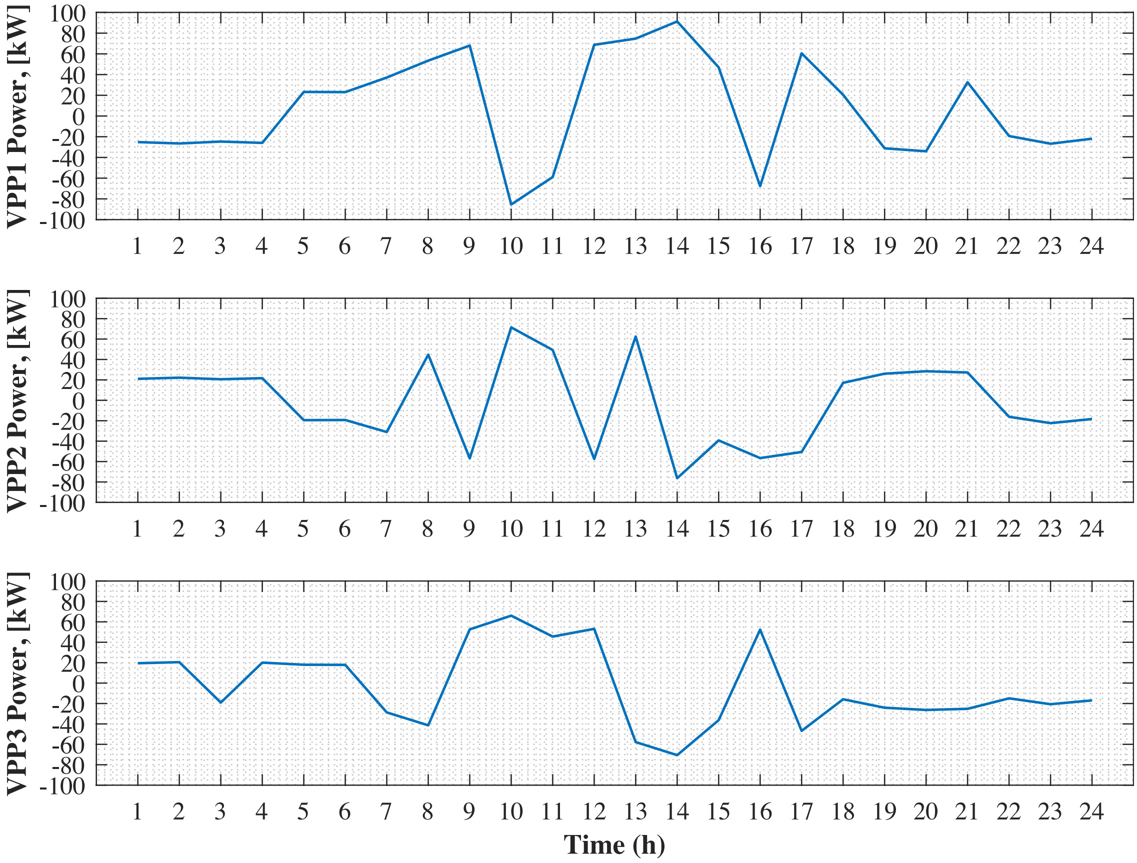


**Figure 3.3 Power states of the VPPs during the day (24 h).**

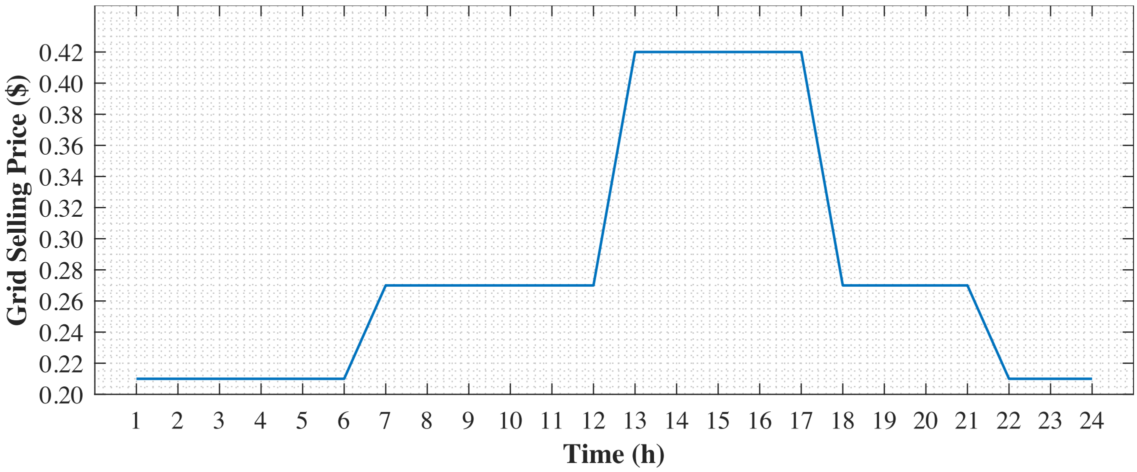


**Figure 3.4 Grid price levels during the day (24 h).**

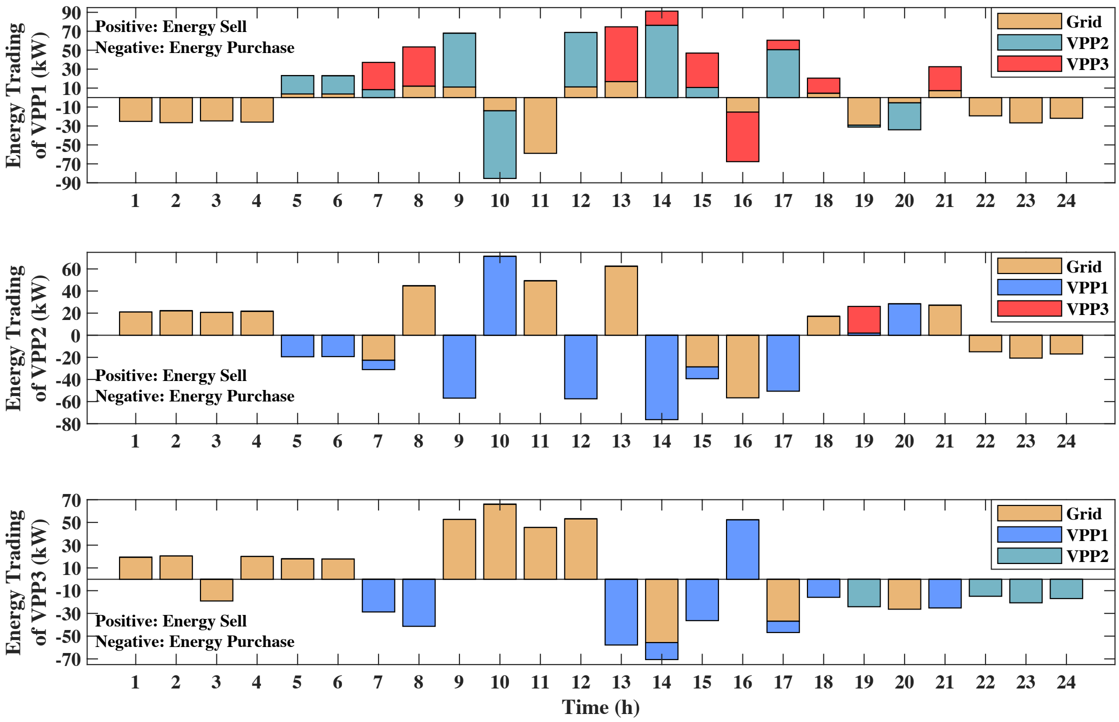


**Figure 3.5 Energy trading of VPPs.**

Figure 3.5 depicts each VPP's overall power exchange with other VPPs and the grid, including the power sold (if positive) and the power purchased (if negative). It is obvious that at hour 1, VPP1 purchased energy from the grid, while VPP2 and VPP3 had excess energy to sell. This is because the grid price is sufficiently low when we compare the VPP2's and VPP3's prices. Therefore, VPP2 and VPP3 must sell their excess energy to the grid. At hour 7, VPP1 had 37.13 kW excess energy, while VPP2 and VPP3 had 31.057 kW and 28.718 kW energy deficits, respectively. At that time, the other VPPs want to fill the energy gap from VPP1 because the grid price is higher than VPP1. While

VPP3 met the entire 28.78 kW energy deficit from VPP1, VPP2 purchased 6.07 kW of its 31.057 KW energy requirement from VPP1 and completes the rest from the grid.

Figure 3.6 illustrates the effect of the number of tokens in the pool on the unit price of the token. As an example, the variation in VPP1 as a result of transactions between VPPs and the grid during a day is shown in the Figure 3.6. Initially, 3.5 AVAX and 1750 TRY1 liquids were added to the AVAX/TRY1 liquidity pool with equal values for the two tokens. The AVAX/TRY1 parity in this case is 500, and the initial unit price of TRY1 is \$0.14. Moreover, the unit price of AVAX is assumed to be \$70 throughout the study. As VPP1 purchased energy from the grid in the first transaction, 35.24 TRY1 tokens were added to the pool, bringing the total amount of TRY1 to 1785.24. In exchange, 0.0688855630513128 AVAX was removed from the pool to pay the grid, leaving 3.431114 AVAX in the pool. An increase in the amount of TRY1 in the pool caused the unit price to decrease to \$0.136832844, while the AVAX/TRY1 parity increased to 520.3090811.

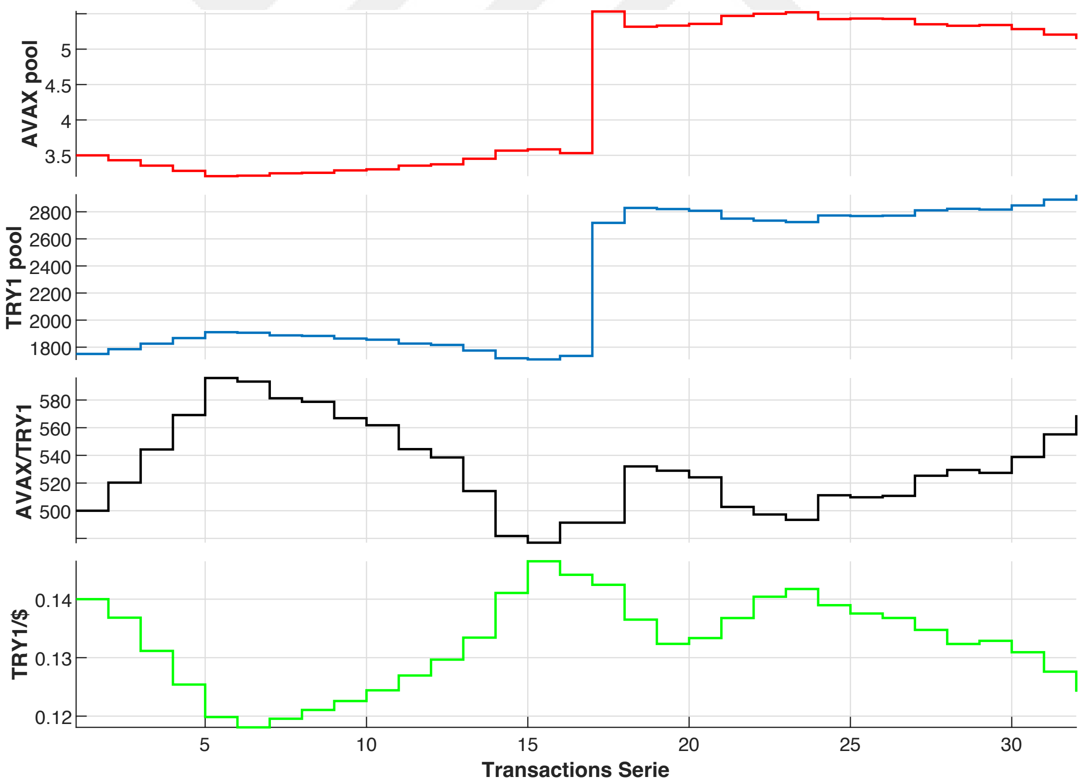


**Figure 3.6 Changes in the parities and pools while swapping transactions during the day (24 h).**

Before the 10th transaction occurred, the pool had 1855.267 TRY1 and 3.302563 AVAX, the AVAX/TRY1 parity was 561.7658462, and the unit price of TRY1 was

$0.124416114. VPP1 sold its excess energy to VPP3, as seen in Figure 3.5 at hour 7; thus, a transaction occurred between VPP1 and VPP3. This poll is a non-AVAX pool, which is why the liquidity was calculated by observing the price of the VPP3 token in comparison to AVAX. Hence, from this exchange between VPP1 and VPP3, VPP3 had to pay 28.718 TRY1 to VPP1, which is equal to 0.052080937AVAX. Consequently, 0.052080937AVAX was added to the pool and 28.718 TRY1 left the pool. At the end of this swap, there was a total of 1826.549257 TRY1 and 3.35464422 AVAX in the pool. The AVAX/TRY1 parity decreased from 561.7658462 to 544.4837477 and the unit price of TRY1 increased from $0.124416114 to $0.126947058.

Liquidity might be added to the pool at any time during the trading flow. Figure 3.6 depicts the salient effect of this addition on pool and parity. In the 17th transaction, we added 982.7653475 TRY1 and 2 AVAX liquidity to the pool. Therefore, the pool has 2718.171754 TRY1 and 5.531680093 AVAX with 491.3826737 AVAX/TRY1 and 0.142455165 TRY1/$ after liquidity addition. This explains the dramatic shift in the 17th transaction in the figure.

Finally, 5.1413 AVAX and 2925.8786 TRY1 remained in the pool owing to the transactions conducted over the day. Additionally, the remaining tokens can be observed in the Avalanche Fuji test network, as shown in Figure 3.7. Further, the AVAX/TRY1 parity increased to 569.0857769, with a daily fluctuation of 13.81715% between the beginning and end of day. Similarly, the unit price of TRY1 fell to $0.12416 at the end of day, declining by 11.31036% owing to an increase in the amount of TRY1 in the pool.

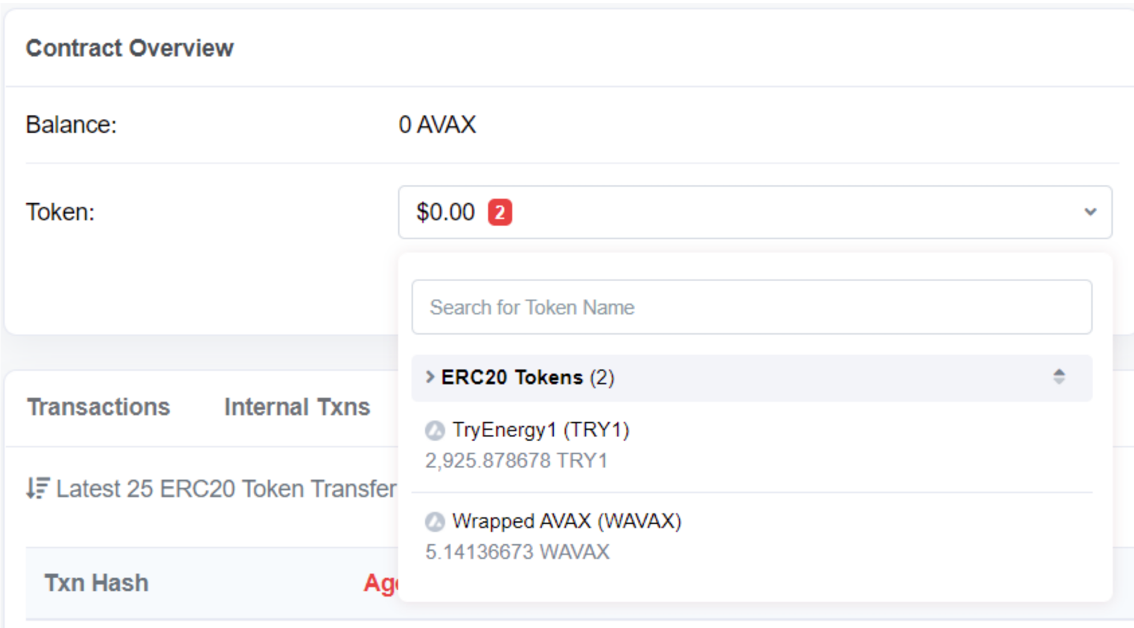


**Figure 3.7 Last token balances in the pool.**

Table 3.1 shows the transactions between the VPPs and grid. These transactions are swapping of VPP specific tokens through the Pangolin DEX to trade energy between VPPs. G, V1, V2, and V3 represent the grid, VPP1, VPP2, and VPP3, respectively. Every column represents transactions occurring between pairs stated in the column head. That is, during the 19th hour of the day, VPP1 swapped 57.36531253 *TRY1* tokens for AVAX to buy energy from the grid. VPP1 again swapped the *TRY1* tokens to 1.964588468 *TRY2* tokens to buy energy from VPP2. Finally, VPP3 swapped *TRY3* for 24.12165254 *TRY2* tokens to buy energy from VPP2. Therefore, the positive and negative signs in the transactions specify the transaction direction.

**Table 3.1 Energy tradings among VPPs.**

| Hour (h) | V1 <> G [TRY1] | V2 <> G [TRY2] | V3 <> G [TRY3] | V1 <> V2 [TRY1/TRY2] | V1 <> V3 [TRY1/TRY3] | V2 <> V3 [TRY2/TRY3] |
|---|---|---|---|---|---|---|
| **1** | -35.24 | 10.95 | 5.62 | 0.00 | 0.00 | 0.00 |
| **2** | -40.69 | 11.35 | 5.85 | 0.00 | 0.00 | 0.00 |
| **3** | -39.86 | 10.27 | -8.56 | 0.00 | 0.00 | 0.00 |
| **4** | -43.44 | 10.52 | 5.68 | 0.00 | 0.00 | 0.00 |
| **5** | 4.13 | 0.00 | 5.08 | 19.45 | 0.00 | 0.00 |
| **6** | 4.16 | 0.00 | 4.96 | 19.30 | 0.00 | 0.00 |
| **7** | 0.00 | -23.08 | 0.00 | 8.41 | 28.72 | 0.00 |
| **8** | 10.06 | 17.50 | 0.00 | 0.00 | 41.37 | 0.00 |
| **9** | 8.58 | 0.00 | 11.88 | 56.89 | 0.00 | 0.00 |
| **10** | -25.76 | 0.00 | 14.41 | -71.44 | 0.00 | 0.00 |
| **11** | -110.33 | 18.08 | 9.52 | 0.00 | 0.00 | 0.00 |
| **12** | 8.24 | 0.00 | 10.67 | 57.48 | 0.00 | 0.00 |
| **13** | 12.79 | 23.40 | 0.00 | 0.00 | 57.79 | 0.00 |
| **14** | 0.00 | 0.00 | -47.16 | 76.33 | 14.93 | 0.00 |
| **15** | 0.00 | -52.03 | 0.00 | 10.64 | 36.33 | 0.00 |
| **16** | -48.65 | -96.61 | 0.00 | 0.00 | -52.34 | 0.00 |
| **17** | 0.00 | 0.00 | -35.45 | 50.62 | 9.90 | 0.00 |
| **18** | 3.94 | 9.17 | 0.00 | 0.00 | 15.85 | 0.00 |
| **19** | -57.37 | 0.00 | 0.00 | -1.96 | 0.00 | 24.12 |
| **20** | -11.13 | 0.00 | -20.01 | -28.47 | 0.00 | 0.00 |
| **21** | 5.58 | 14.94 | 0.00 | 0.00 | 25.20 | 0.00 |
| **22** | -30.53 | -17.46 | -7.23 | 0.00 | 0.00 | 0.00 |
| **23** | -42.90 | -24.38 | -12.80 | 0.00 | 0.00 | 0.00 |
| **24** | -36.06 | -20.86 | -10.78 | 0.00 | 0.00 | 0.00 |

## 3.6 Conclusions

In this study, an inter-VPP trading platform scheme and flow were developed to achieve efficient, transparent, and economic P2P energy trading between the same or different blockchain based VPP frameworks without the supervision of the intermediaries. A DEX (Pangolin) running on a public blockchain platform (Avalanche), unlike other studies and applications in the extant literature, is utilized for the implementation. The primary purpose of this study is to demonstrate the feasibility of P2P trading with professional Defi instruments in current use. In line with this purpose, the entire flow was tested by making the token swaps via Pangolin and transactions on a realistic test network named Fuji of the Avalanche Platform. These transactions were performed according to the case study's MILP-based power optimization model results. Obviously, the parity of the tokens against each other is shaped by the initial ratios of the pools on the DEX and the supply-demand balance that emerges after the swaps. Graphs showing these parity variations of tokens while swapping transactions are crucial and justifying outcomes for the proposed scheme. As the focus of this study was on the applicability and implementation of inter-VPP trading with DeFi blessings, trading advertisement requirements for sellers and buyers are still present in this scheme and flow, which can be easily overcome with off-chain solutions. Utilizing software controlled by an authority or a decentralized, intermediary-free blockchain structure with SCs can be necessary for the purchaser and vendor to peer with each other. This issue, intra-VPP optimization, and more technical drawbacks and impacts of DEXs on energy trading can be investigated in future studies.

# Chapter 4

# Deep Learning to Optimize Peer-to-Peer Energy Trading via a Decentralized Exchange among Virtual Power Plants

In this study, we propose a novel approach to accelerate the optimization of peer-to-peer (P2P) energy trading among Virtual Power Plants (VPPs) by combining Mixed Integer Linear Programming (MILP) with Machine/Deep Learning (ML/DL) models. The VPPs trade energy with each other through Decentralized Exchanges (DEX), exchanging their specific tokens while maintaining a balance between energy supply and demand. The MILP optimization problem accounts for DEX swaps and token pair value changes, to ensure cost-minimized energy trading. However, solving the optimization problem using MILP can be computationally expensive and time-consuming. As a result, we use ML/DL models trained on the optimization results to quickly address additional optimization problems that arise later in the trading process. Our approach aims to improve the scalability and efficiency of P2P energy trading in microgrids, paving the way for a more sustainable and decentralized energy system.

## 4.1 Introduction

Distributed generation has been promoted as a reliable alternative to traditional forms of generation, owing to rising energy demand and increased awareness of sustainability, as well as technological advancements in energy storage and the growth of smart grids, including microgrids and virtual power plants (VPPs). Therefore, the current old and cumbersome centralized power system is undergoing a significant transformation, driven by the increasing development and deployment of microgrids and virtual power plants. In addition, distribution grids have been gradually integrating distributed energy resources (DERs) in recent years. Numerous factors contribute to the mentioned tendencies:

- Energy is increasingly strengthening its strategic position in each country [121], [122].
- Global warming and climate change are becoming apparent worldwide. Thus, the tendency to use renewable energy sources (RESs) instead of fossil fuels is growing [121]–[123].
- Recent tragic events around the world demonstrate that governments and regions with energy shortages must integrate even more flexible and distributed energy solutions into their energy production to avoid relying on other countries and regions [121], [122].
- Residential rooftop photovoltaic panels (PVs), energy storage systems (ESSs), heat pumps, and small-scale wind turbines have fostered the number of prosumers who have the flexibility to be producers or consumers according to their needs [124]–[126].
- More electric vehicles (EVs) will be integrated into the grid by citizens, resulting in a new type of DER that will soon increase the number of transfers from vehicles to the load or grid and vice versa [127]–[129].
- The demand for increased power system reliability and flexibility, as well as the emergence of new business models that enable the integration of DERs, is growing [69], [72], [125], [126], [130].

DERs, such as small-scale power generation units and ESSs, have gained popularity as they located near the end-user. The adoption of DERs has a substantial impact on the energy infrastructure, leading to a decentralized, coordinated, and environmentally friendly energy system. The deployment of DERs contributes to power system stability and reliability, lowers energy waste, increases energy efficiency, and encourages renewable energy production. However, incorporating DERs presents certain challenges, including handling bidirectional power flows and integrating novel technologies with the existing grid infrastructure. Despite these difficulties, DERs are expected to continue as a major driving force behind the transformation of the energy sector [130], [131]. The combination of smart grid technologies and DERs creates a mutually beneficial relationship. Smart grid technology improves the integration and management of DERs, while DERs offer increased flexibility and resilience to the grid. This collaboration results in a more efficient, reliable, and sustainable energy infrastructure that adapts to the evolving energy needs of society [132]. Smart grids enhance real-time communication between utilities and customers, improving electricity management. Integrating RESs, EVs, and ESSs reduces greenhouse gas emissions [133]. Furthermore, smart grids have played an important role in laying the groundwork for the emergence of microgrids and VPPs. Microgrids can consist of different types of DERs, and they can operate stand-alone (islanded) or in conjunction with the main grid. Microgrids are frequently utilized in isolated places where the main grid is unavailable, or for critical infrastructure such as data centers, healthcare, and military facilities [69]. On the other hand, VPPs surfaced in the mid-2010s as an innovative way to aggregate and manage DERs through advanced software and communication technologies. VPPs create a flexible, cloud-based platform, combining diverse DERs into a single, coordinated power plant. This enables real-time monitoring and control of DERs, allowing for dynamic energy trading and management while also providing ancillary services to the grid, such as frequency regulation and voltage control. VPPs signify a considerable step towards decentralized energy management, optimizing energy resources and reducing reliance on large, centralized power plants [72]. In addition to these breakthroughs, peer-to-peer (P2P) energy trading has arisen, enabling prosumers and consumers to directly buy and sell energy without the need for a governing body. In line with the decentralized nature of P2P energy trading, blockchain technology enables safe and transparent P2P payments. Several research studies and technology businesses have rated blockchain-based P2P trading as one of the most promising platforms for decentralized energy management systems (EMS) [134]. Leveraging the capabilities of optimization, artificial intelligence techniques, namely machine learning (ML)/deep learning (DL), and blockchain technologies for energy trading can help increase the adoption of RES by making P2P trading more efficient and profitable, encouraging consumers to produce and sell excess energy. Furthermore, they can help reduce the burden on centralized EMS while providing economic incentives to prosumers [126], [133].

In this manner, optimization techniques and algorithms are commonly employed in P2P energy trading research to improve efficiency and minimize costs. The general goal is to determine the optimal set of transactions between peers, considering factors such as energy demand and supply, pricing, and the constraints of the energy trading network. By optimizing these factors, researchers mostly aim to maximize social welfare and overall profitability for all participants in the P2P energy trading network, ultimately contributing to more sustainable and cost-effective energy system.

For example, in [135], researchers address the problem of optimizing energy costs in smart homes connected for energy sharing. They propose a new almost optimal algorithm that decomposes their previously proposed optimal model (a non-convex mixed integer nonlinear programming model) into multiple Mixed Integer Linear Programming (MILP) modules that coordinate P2P energy trading with lower time complexity. However, their proposed approach is developed for a centralized architecture (e.g., cloud). Yan et al. proposed a two-level network-constrained transactive energy market for multi microgrids based on centralized optimization methods, where a market operator directly collects all the information and optimizes microgrid DERs. To address privacy concerns, only limited information exchanged with the market operator, which is sufficient for managing the microgrids but does not compromise their privacy [136]. Huang et al. made a P2P electricity trading system based on coalition game theory to figure out the trading price based on the minimum total amount of energy used in microgrids in different situations. They used MILP model again to find the best price to buy and sell energy in a microgrid over a period of 24 hours as real-world constraints change [137]. Yet, their research requires a central authority and does not involve any decentralized blockchain technology. The study in [138] offers a two-stage P2P energy trading model comprised of a local scheduling problem modeled as MILP and a price adjustment mechanism for energy trading between microgrids. The model is validated through simulation using 24-hour anticipated net load data from seven networked microgrids, incorporating their shortfall and excess power that cannot be exchanged with the utility grid due to tie-line limitations. Similarly, a two-stage optimization approach is used to determine who participate in P2P trading and the amounts of exchanged energy taking the social utility maximization as the objective function at first stage, and then gain the optimal trading payoffs in [139]. Likewise, in [140], the authors suggested a novel P2P EMS across buildings that takes into account the multi-energy connection of electrical power, heating and cooling demands, and micro sources. Other peers' trading tactics in P2P energy trading are built up as a parameter optimization problem that can be translated into the MILP formulation, and an auxiliary optimization model based on maximizing total profit is constructed. Nevertheless, the time and computing complexity of such a model and optimization process is not stated. In the study [126], the proposed approach utilizes local execution of fuzzy logic and optimization algorithms, avoiding any hindrance to the main computational system. Load and generation scheduling methods are provided for various end-users, including residential, commercial, industrial, and EV aggregators. Simulation results reveal that the suggested model outperforms a traditional power system when applied to a hybrid power system. Using a single server, the longest path was 6 minutes and 55 seconds, and the authors expect the time complexity to decrease dramatically with parallel computing.

Also, researchers use distinct types of methods to achieve more robust and faster solutions for optimization as in [85], a multi-agent system uses an algorithm based on a multi-objective Bat algorithm, Pareto front, and fuzzy decision-making algorithm. The paper also includes four case studies to validate and prove that the proposed scheme works faster, providing comparisons with other algorithms. In [141], proposed model for multi objective optimization is levelized cost of energy and reliability index. These benchmarks are considered for optimization to determine the correct sizing of distributed energy resources (DERs) and optimum payoff values. The simulation model is built in MATLAB software, and the particle swarm optimization is exploited.

According to the findings of [142], P2P trading in conjunction with Vehicle to Home (V2H) offers significant benefits; hence, P2P can serve as a catalyst for increasing PV and EV ownership. With the decline of internal combustion engine vehicles and the proliferation of EVs, there will be more actors in the energy trading scene. That will further complicate P2P energy trading and increase the need for instant and efficient optimization approaches [129]. Indeed, in the study [143], researchers aimed to develop multi-objective P2P trading optimizations for renewable energy systems with hybrid energy storage of hydrogen and battery vehicles to find optimal configurations of vehicle numbers in diversified building groups and time-of-use (TOU) management operations, for a comprehensive optimization considering the system supply, electricity cost, and decarbonization benefits.

Researchers even investigate how EVs and shiftable loads affect P2P energy trading with increased V2H mode and present an optimized EMS to reduce grid energy exchange. MILP is used to optimize energy scheduling for community smart dwellings [144]. They report that using EVs in trading as storage sources and not only as loads reduces prosumer's costs by 23% and community energy bills by 15%.

As can be seen from the cited studies, optimization is mostly used to reduce the cost of energy trading for peers, but often the computational complexity is not considered. Our previous paper also used MILP-based optimization to plan energy transfers between

VPPs according to the case study's energy profile to minimize costs [7]. We proposed an inter-VPP P2P trading scheme between the same or different blockchain-based VPP frameworks without the supervision of intermediaries, taking advantage of the blessings of Decentralized Finance (DeFi), especially Decentralized Exchange (DEX). However, the main limitation in performing optimizations is the high computational complexity due to the nature of mathematical programming, and even in some cases (high number of agents/peers) optimizations may not be feasible solutions.

In this regard, a new approach is needed to make trading scalable, run faster on the microcomputers of intelligent trading agents (smart meters and devices needed to realize P2P energy trading), and avoid using general optimization techniques that are slow or fail in scenarios with multiple actors. The present study puts forward a new approach that proposes to use ML/DL models as complementary practices to traditional mathematical programming techniques for the optimization of energy trading schedules. The primary motivation for this research is to address the high computational complexity and occasional infeasibility of optimization solutions using conventional methods. By incorporating optimization results into ML/DL models, we aim to mitigate these problems while maintaining and even improving the overall efficiency of the system. Ultimately, this approach aims to improve the effectiveness of real-time energy trading operations. The goal of this study is to highlight the benefits and viability of using ML/DL models to optimize P2P energy trading.

Our proposed approach explores various regression and neural network-based models for optimizing P2P energy trading schedules within the context of our previously proposed inter-VPP trading scheme utilizing Decentralized Exchanges (DEX) on a public blockchain platform. The goal is to determine the practicality of employing ML/DL models in P2P trading scenarios and assess their performance compared to traditional optimization methods. The main contributions of this study are as follows:

- We propose a novel approach of utilizing ML/DL models as alternative methods to traditional optimization techniques for energy trading schedule optimization in P2P energy trading systems.
- We present the possible practical benefits and computational time improvements of using ML/DL models as a complement to P2P energy trading optimization and highlight how this approach can reduce computational complexity and improve decision-making based on optimization outcomes in energy trading scenarios.

- We investigate the use of several regression and neural network-based models and evaluate their applicability and effectiveness in DEX-based P2P energy trading optimization situations.
- We compare the accuracy, computation time, and viability of solutions between ML/DL models and conventional mathematical programming technique.

Following the introduction section, which include a literature review as well, Section 4.2 furnishes the contextual background information. Section 4.3 presents the methodology and proposed approach for optimizing energy transactions between VPPs and the grid. Section 4.4 presents our finding and analysis, including the ML/DL models utilized and the metrics to measure their performance. Finally, the research will culminate in Section 4.5, where we will provide a synopsis of our discoveries and deliberate on conceivable future avenues.

## 4.2 Background Information

This section presents a concise overview of the fundamental concepts and technologies associated with our research, including Pangolin, the Constant Function Market Maker (CFMM) model, Decentralized Exchanges (DEXs), and their relevance within the DeFi ecosystem.

### 4.2.1 Decentralized exchange (DEX)

A DEX is a type of DeFi platform that operates on a blockchain network, allowing coins and tokens to be swapped directly between users without intermediaries. DEXs utilize smart contracts and Automated Market Makers (AMMs) to execute trades, providing users with enhanced security, privacy, and ownership over their assets. DEXs have gained significant traction within the cryptocurrency ecosystem, providing a more inclusive and accessible financial platform for users worldwide. Despite their potential, certain challenges remain, and ongoing refinements to their operational mechanisms and AMMs are essential for continued growth and stability.

### 4.2.2 Pangolin and uniswap

Pangolin, a DEX developed on the Avalanche blockchain network later supported multi-chain, utilizes the Constant Function Market Maker (CFMM) model, which is a specific type of AMM. The CFMM model, characterized by a constant product formula that keeps the product of the quantities of the two assets in the pool constant, is also used by well-known DEX platforms like Uniswap [145], [146]. As given in Equation (4.1), $x$ and $y$ represent the quantities of the two tokens in the pool, and $k$ is a constant. This formula ensures that the relative token prices in the pool automatically adjust as trades are executed, providing instant liquidity, and minimizing slippage. When someone wants to trade token $x$ for token $y$, they must deposit an equivalent value of both tokens ($\Delta x$ and $\Delta y$) into the pool. This changes the values of $x$ and $y$, but the product $k$ remains the same. The new values of $x$ and $y$ are calculated in Equations (4.2) and (4.3). *Fees* are charges imposed on trades to incentivize liquidity providers and sustain the pool. The *fee* is typically a percentage of the transaction value and is distributed among the liquidity providers as a reward for their participation. The new exchange rate between token $x$ and token $y$ can be determined by dividing the new value of $y$ by the new value of $x$ as given in Equation (4.5).

$$x * y = k \tag{4.1}$$

$$new\_x = x + \Delta x + fee \tag{4.2}$$

$$new\_y = \frac{k}{new\_x} \tag{4.3}$$

$$\Delta y = y - new\_y \tag{4.4}$$

$$newExchangeRate = \frac{new\_y}{new\_x} \tag{4.5}$$

In the CFMM model, liquidity pools are created for each trading pair of tokens, and users trade against these pools instead of directly with each other. Liquidity providers (LPs) supply the pools with assets and receive LP tokens representing their share of the pool. These LP tokens can be redeemed for their proportionate share of the pool's assets plus any accrued trading fees.

In our previous paper [7], we proposed an inter-VPP P2P trading scheme that leverages the Pangolin DEX. By utilizing the DeFi blessings like bridges, our proposed system enables P2P energy trading between same and different blockchain-based VPP frameworks without the need for intermediaries, thus reducing costs and improving efficiency.

In the current study, we further explore the potential of ML/DL techniques as complementary or alternative methods for optimizing energy trading schedules in the context of the inter-VPP P2P trading scheme. By evaluating the performance of various ML models and comparing them with traditional optimization methods, we aim to develop more efficient and scalable P2P energy trading systems that can overcome the limitations posed by traditional optimization techniques in terms of computational complexity and feasibility of solutions.

## 4.3 Methodology

This study aims to achieve optimal energy transactions between three Virtual Power Plants (VPPs) and the grid in a system by leveraging blockchain and DeFi. Each VPP mints its own specific token on the Avalanche C-chain: TRY1, TRY2, and TRY3 for VPP1, VPP2, and VPP3, respectively. These tokens are collectively called Try Energy Tokens (TRY). The VPPs sell their excess power to one another or the grid, pricing their power using their specific token. The tokenization of energy effectively allows VPPs to trade with each other in a decentralized manner, optimizing their operations and minimizing energy costs. The exchange rate / parity between the different VPP tokens occurs within the Pangolin DEX according to the supply and demand dynamics of the tokens in the liquidity pools.

In this study, we have three pools which are AVAX/TRY1, AVAX/TRY2, and AVAX/TRY3. Each of these pools is associated with a different VPPs. At the beginning, all three pools contained the same amount of liquidity - specifically, 1000000 tokens and 7500 AVAX. This means that the initial ratio of tokens to AVAX within each pool was 133.33 (i.e., each pool contained 133.33 tokens for every 1 AVAX). The initial unit price of tokens was \$0.15, and for the purpose of this study, we have assumed that the unit price of AVAX remains fixed at \$20.

### 4.3.1 Mixed integer linear programming formulation

The objective function (*Cost*) in this study is based on (4.6), where the variables are defined as follows: $i \in \{0,1,2,3\}$ is the number of prosumers in the system, $P_{ij,t}$ is the energy to be transferred from prosumer $j$ to prosumer $i$ at time $t$, and $\gamma_j$ is the unit energy price of the prosumer selling the energy. The purpose of this equation is to minimize the total energy cost of the proposed system by optimizing both the energy consumed from the grid and the energy costs associated with transfers between prosumers, while accounting for the energy prices of each prosumer and the grid.

Since a prosumer can either be a seller of energy (i.e., they have excess energy that they can sell) or a buyer of energy (i.e., they need more energy than they can produce), the variable $u_i$ in constraint (4.7) is the binary variables that is used to indicate the seller-buyer status of prosumer: $u_i$ = 0 indicates that prosumer *i* is a seller, and $u_i$ = 1 indicates that prosumer *i* is a buyer.

Constraints (4.8) and (4.9) provide the limits on the amount of energy that can be transferred between prosumers, $P_{ij,t}$, based on their seller-buyer status and the intended amount of the selling or purchasing energy, $P^a_{i,t}$. Specifically, if prosumer *i* is a buyer ($u_i$ = 1), then the amount of energy they can purchase from prosumer *j* (where *j* ≠ *i*) at time *t* is limited by constraint (4.8). On the other hand, if prosumer i is a seller ($u_i$ = 0), then the amount of energy they can sell to prosumer j (where j ≠ i) at time *t* is limited by constraint (4.9).

The power balance equations are also considered as in constraints (4.10) and (4.11). Thus, it can be ensured that the total energy supplied to the system (i.e., the energy produced by the prosumers and purchased from the grid) matches the total energy consumed by the system (i.e., the energy used by the prosumers).

Minimize $$Cost = \sum_i \sum_{j \neq i} \left(P_{ij,t} \cdot \gamma_{j,t}\right) \tag{4.6}$$

Subject to $$u_i \in \{0,1\} \quad \forall i \tag{4.7}$$

$$P_{ij,t} \leq \left(1 - u_{i,t}\right) \cdot P^a_{i,t} \qquad \forall i, \forall t \tag{4.8}$$

$$P_{ij,t} \geq u_{i,t} \cdot P^a_{i,t} \qquad \forall i, \forall t \tag{4.9}$$

$$\sum_i \left( \sum_{j \neq i} P_{ij,t} = P^a_{i,t} \right) \qquad \forall i, \forall t \tag{4.10}$$

$$\sum_i \sum_{j \neq i} \left(P_{ij,t} + P_{ji,t}\right) = 0 \qquad \forall i, \forall t \tag{4.11}$$

### 4.3.2 Dataset

The dataset used in this study contains 69,120 rows and was divided into training and test sets with an 80:20 ratio. Within the training set, 20% was used for validation. It includes historical energy deficiency and surplus data from multiple Virtual Power Plants (VPPs) participating in the inter-VPP P2P trading scheme, with eight independent input features, including VPP power states, purchase price from the grid, sale price to the grid, and price of each token. Regression models were fitted to predict six dependent variables corresponding to the amount of energy traded between VPPs and the grid.

### 4.3.3 Proposed approach

As can be seen in the flowchart of the proposed approach in Figure 4.1, for the ML regression models, we first need to generate data including input data and corresponding targets. To do this, the problem is formulated as a MILP as mentioned above and solved with the Coin-or-Branch and Cut (CBC) solver using the PuLP library, an open-source linear programming modeler package in Python [147], [148]. The MILP optimization is performed based on the input data, then the corresponding targets are obtained as a result of the optimization. According to the outputs, it is calculated which peer will send how many tokens to which peer in return for the energy cost. After the computation, these swaps take place by means of the DEX, which is mathematically modeled and coded in Python. The changes in the pools are observed after the transactions and the parities are calculated. The changing unit prices of the tokens are then sent to the MILP to form the next inputs, and the data is saved to a dataset file. This process continues until the data in the file is finished. After the data preparation process, we preprocess the generated dataset and create appropriate input and output variables for training and evaluating the ML and DL models.

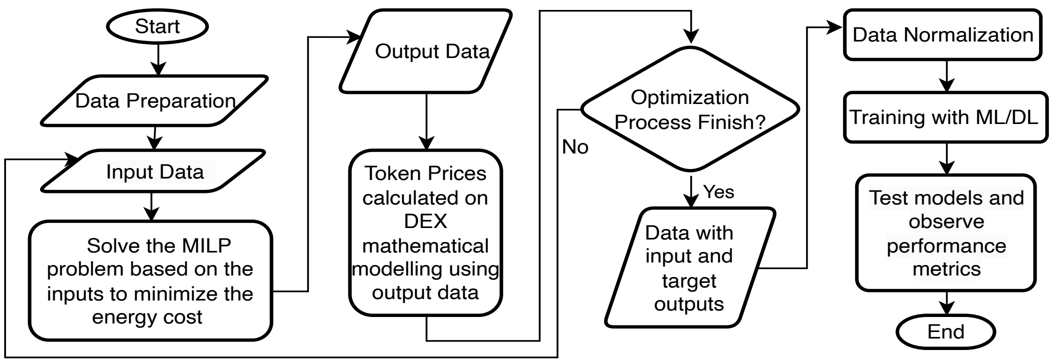


**Figure 4.1 Flowchart of the proposed approach.**

Then, ML regression models used in this study, linear regression (LR), k-nearest neighbors (KNN), support vector machine (SVM), and DL methods, are trained by providing training data. After the training process is done, test data is given to the fitted model and performance metrics often used in regression, $R^2$ score, adjusted $R^2$ score, mean absolute error, mean squared error, root mean squared error and explained variance score, are calculated to observe how well it predicts.

## 4.4 Results and Discussion

Table 4.1 shows the performance metrics of the used methods. The $R^2$ score, adjusted $R^2$ score, and explained variance score are measures of how well the model fits the data, with a higher score indicating a better fit. The CNN and LSTM models both have the highest scores across all three metrics, suggesting that they fit the data better than the other models. The $R^2$ score for the CNN model is 0.99562, which is significantly higher than the next highest score of 0.98276 for the DNN model. In comparison, the other models had $R^2$ scores ranging from 0.62867 to 0.98276. The adjusted $R^2$ score and explained variance score show a similar pattern of results.

**Table 4.1 Performance metrics of the methods used.**

| Metrics \ Methods | Lin. Reg. | SVM | KNN | DNN | CNN | LSTM |
|---|---|---|---|---|---|---|
| $R^2$ score | 0.62867 | 0.90923 | 0.97991 | 0.98276 | 0.99562 | 0.99287 |
| Adjusted $R^2$ score | 0.62848 | 0.90918 | 0.97990 | 0.98275 | 0.99561 | 0.99290 |
| Expl. Variance Score | 0.62871 | 0.90931 | 0.97992 | 0.98282 | 0.99573 | 0.99290 |
| Mean Abs. Err. | 3.12618 | 1.07505 | 0.50927 | 0.22479 | 0.22428 | 0.14487 |
| Mean Sq. Err. | 23.24082 | 5.59771 | 1.81509 | 0.91118 | 0.23388 | 0.30271 |
| Root Mean Sq. Err. | 4.73486 | 2.32120 | 1.23660 | 0.93909 | 0.47436 | 0.54177 |

The mean absolute error, mean squared error, and root mean squared error measures assess the difference between the predicted values and the actual values, with lower scores indicating better performance. Similarly, the CNN and LSTM models have the lowest scores across all three metrics, indicating that they have the lowest error rates. While the mean squared error for the CNN model is only 0.23388, the biggest score is 23.24082 for the linear regression model. The CNN and LSTM models have only mean absolute errors of 0.22428 and 0.14487, respectively, while the other models have mean absolute errors ranging from 0.50927 to 3.12618.

To visualize the how the models fit the test data, heat map is used to understand better as shown in Figure 4.2. In this map, while Power10 indicates the predicted data by models, Power10* gives the targets of the data. Power10 indicates the amount of power transferred from VPP1 to the grid if the value is positive. If the value is negative, it's the amount of power transferred from the grid to VPP1.

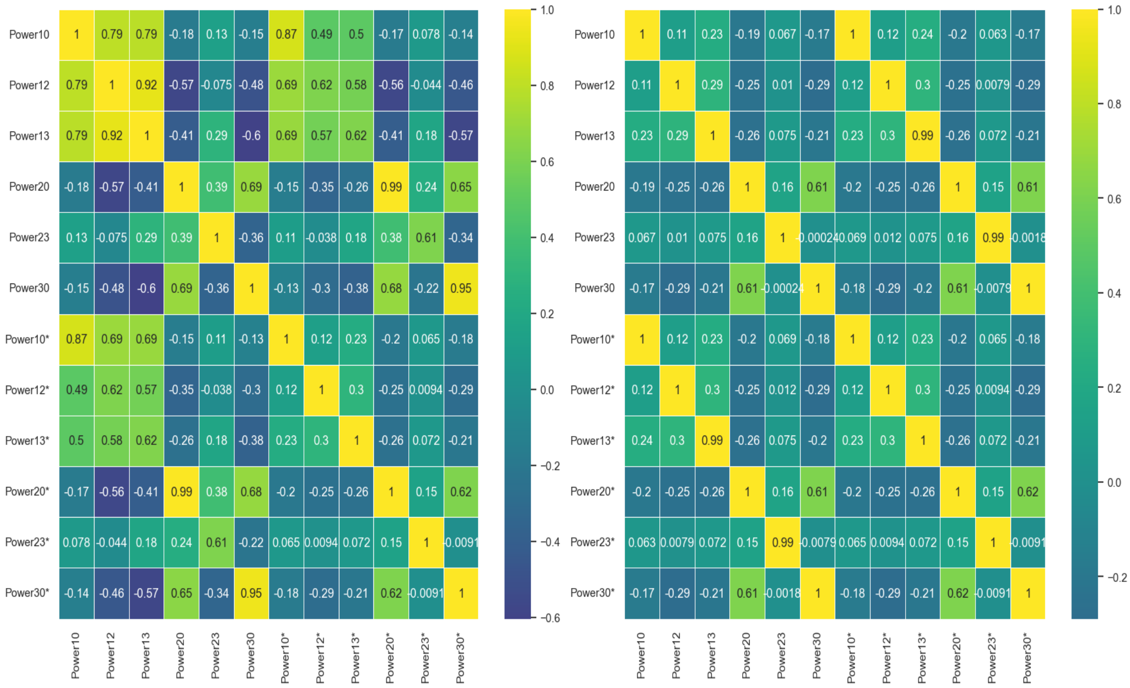

**Figure 4.2 Performance metrics of the methods used.**

Table 4.2 shows the training and testing durations for each of the models used in the study. The training duration refers to the amount of time it took to train the model on the training dataset, while the test duration refers to the amount of time it took to evaluate the model on the test dataset. The MILP optimization has no training process and has the longest average test time at 377.1281 seconds. The linear regression model has a training duration of 0.1403 seconds and a test duration of 0.0312 seconds, while the KNN model had a training duration of 1.0277 seconds and a test duration of 1.9820 seconds, making them the models with the shortest training and test durations, whereas the SVM, DNN, CNN, and LSTM models all have much longer durations. The SVM model has the second longest average test duration at 315.5816 seconds, with a training duration of 845.6562 seconds. The DNN, CNN, and LSTM models all have training durations of over 1000 seconds, with the LSTM model taking the longest at 3971.2439 seconds. Based on the average daily cost, the MILP method has the lowest average daily cost of $223.314 and is considered the benchmark for comparing the other methods. The relative change in the average daily cost is calculated for each method compared to MILP. The results show that the linear regression method has the highest average daily cost of $263.966, which is 18.20% higher than the MILP method. LSTM has the lowest relative change with a 0.78% variation in average daily cost, followed by CNN with a 2.51% variation in cost. KNN and DNN show a relative change of 10.10% and 4.95% respectively, while SVM has a 7.08% relative change in average daily cost compared to MILP. Table 4.3 shows the hyperparameters for each of the models used in the study.

**Table 4.2 Training and test duration of the methods used.**

| Methods \ Duration | Training (s) | Test (s) | Average daily cost ($) | Relative change (%) |
|---|---|---|---|---|
| **MILP** | - | 377.1281 | 223.314 | - |
| **Lin. Reg.** | 0.1403 | 0.0312 | 263.966 | 18.20 |
| **SVM** | 845.6562 | 315.5816 | 207.501 | 7.08 |
| **KNN** | 1.0277 | 1.9820 | 245.873 | 10.10 |
| **DNN** | 1198.2421 | 1.3752 | 234.372 | 4.95 |
| **CNN** | 1207.3818 | 1.2114 | 228.926 | 2.51 |
| **LSTM** | 3971.2439 | 3.1841 | 221.669 | 0.73 |

**Table 4.3 Hyperparameters of the methods.**

| Hyperparameters \ Methods | DNN | CNN | LSTM |
|---|---|---|---|
| **Learning rate** | 0.001 | 0.001 | 0.001 |
| **Activation function** | RELU | RELU | RELU |
| **Nu. of hidden layers** | 2 | 3 | 3 |
| **Nu. of units in each layer** | 32/64 | 64/128/32 | 64/128/32 |
| **Optimizer** | ADAM | ADAM | ADAM |
| **Epoch Number** | 250 | 250 | 250 |

All study has been simulated and tested using Python 3.9.16 on 64-bit Windows based computer with 16 GB of RAM and 2.70 GHz Intel® Core® i7-6820HQ CPU in order to resemble a smart agent's small scale computing power.

# 4.5 Conclusion

In conclusion, this study presents a novel approach to optimizing energy transactions between Virtual Power Plants (VPPs) and the grid by leveraging blockchain technology, DeFi, and machine learning methods. The results indicate that the proposed framework, which combines mixed-integer linear programming (MILP) optimization and ML/DL models, can effectively facilitate decentralized energy trading, and minimize energy costs for the participating VPPs.

The study finds that the CNN and LSTM models outperform other methods in terms of prediction accuracy and error rates, showcasing their potential for improving the efficiency of the decentralized energy trading system. While these models require more time to train, their outperformance in the tests demonstrates their potential for instant live usage in the real-world energy market settings. Furthermore, the MILP method is utilized as a baseline to compare the average daily cost of energy transactions. It is clear that the LSTM model has the least relative change in average daily cost compared to MILP.

This work also highlights the merits of deploying decentralized platforms like Avalanche C-chain and Pangolin DEX to promote fast, secure, and transparent energy transactions between VPPs. By tokenizing energy, VPPs can optimize their operations and reduce energy costs by trading with each other in a decentralized manner.

Overall, this work demonstrates a potential technique to optimizing energy transactions in a decentralized system and gives useful insights into the use of ML/DL models in the energy industry. Future research could concentrate on improving the proposed models, addressing scalability concerns, and investigating the integration of this approach into existing energy market infrastructure to improve the efficiency, transparency, and sustainability of energy transactions. Furthermore, investigating the feasibility of using reinforcement learning or other advanced learning techniques to adaptively optimize energy trading schemes in response to changing market conditions and evolving VPP and prosumer behavior could be beneficial.

# Chapter 5

# Conclusions and Future Prospects

## 5.1 Conclusions

The dissertation provides a thorough examination of the utilization of blockchain-based platforms in facilitating P2P energy trading within the framework of VPPs. The topic under consideration was explored in four distinct chapters, each providing distinct perspectives on the obstacles and possibilities inherent in this nascent field of inquiry.

Chapter 1 presented a comprehensive overview of the research problem and contextualized it with relevant background information, highlighting the significance of the research in the respective field. It also outlined the research questions and objectives of the study, as well as the methodology used to address these questions.

In chapter 2, a blockchain-based bidding platform and cryptographic testing environment for P2P energy trading within the VPP framework were developed. The feasibility of using Smart Contracts to facilitate P2P energy trading via auction-based bidding mechanisms was demonstrated, and showed how this platform could be used to address both cost and security concerns.

In chapter 3, an inter-VPP trading platform scheme and flow that enables efficient, transparent, and economic P2P energy trading between different blockchain-based VPP frameworks without intermediaries' supervision were proposed. A DEX (Pangolin) running on a public blockchain platform (Avalanche) was utilized to demonstrate the feasibility of P2P trading with professional Defi instruments currently in use.

In chapter 4, blockchain technology, DeFi, and machine learning methods were leveraged to optimize energy transactions between VPPs and the grid. The proposed framework, which combines mixed-integer linear programming (MILP) optimization and ML/DL models, can effectively facilitate decentralized energy trading, and minimize energy costs for the participating VPPs. The results indicated that the CNN and LSTM models outperformed other methods in terms of prediction accuracy and error rates, showcasing their potential for improving the efficiency of the decentralized energy trading system.

Overall, this thesis provides valuable insights into the potential of blockchain-based platforms for P2P energy trading in VPPs. The feasibility of using Smart Contracts, DEXs, and ML/DL methods to achieve efficient, transparent, and economic energy trading while minimizing energy costs was demonstrated. The work highlights the significant role that blockchain technology can play in the transition to a more decentralized, sustainable, and efficient energy system. As the field continues to evolve, it is expected that the work will inspire new ideas and innovative solutions to further enhance the efficiency, transparency, and sustainability of energy transactions in VPPs.

## 5.2 Societal Impact and Contribution to Global Sustainability

Reducing greenhouse gas emissions in power generation is central to the positive environmental impact of VPPs and P2P energy trading. Even though RESs have expanded rapidly in recent years, fossil fuels like coal, oil, and natural gas still accounted for about 80% of global energy use in 2021. Increased energy-related greenhouse gas emissions have exacerbated the peril of climate change, and our heavy reliance on fossil fuels is a significant contributor. VPPs and P2P energy trading provide a promising opportunity to more efficiently integrate DERs, specifically RESs, into the power grid, thereby reducing reliance on fossil fuels. Blockchain-based P2P energy trading applications facilitate transparent energy trading and incentivize greater consumer participation in power generation. This transition is essential to mitigate the effects of global warming, making VPPs and P2P energy trading instrumental in reducing greenhouse gas emissions, particularly CO2, NOx, and SO2.

P2P energy trading inside and among VPPs can benefit society by bringing clean, inexpensive power to populations in underprivileged areas with poor or non-existent electricity infrastructure. These regions stand to benefit economically and in terms of quality of life if they take use of RESs and encourage local energy generation. Hence, this dissertation is strongly aligned with the United Nations (UN) Sustainable Development Goal (SDG) 7 and SDG 13, which aim to “ensure access to affordable, reliable, sustainable, and modern energy for all” and “take urgent action to combat climate change and its impacts,” respectively. More specifically, this research contributes to targets 7.1

and 7.2 of SDG 7. Promoting the integration of RESs and DERs through VPPs and P2P energy trading, it supports the expansion of electricity access to underserved populations (indicator 7.1.1) and the increased adoption of clean fuels and technologies (indicator 7.1.2). In addition, it contributes to target 7.2, which seeks to "increase substantially the share of renewable energy in the global energy mix" by 2030. Furthermore, it aims to promote the integration of renewable energy sources into the global energy landscape by developing and showcasing the advantages of P2P energy trading with blockchain technologies in supporting the electricity grid. The ultimate objective is to increase the proportion of renewable energy in the total final global energy consumption rate.

In summation, the studies presented in this thesis contribute to global sustainability by promoting the efficient integration of renewable energy sources and DERs through VPPs and blockchain-based P2P energy trading, reducing greenhouse gas emissions, and supporting the UN SDGs. They help shape the future of sustainable, decentralized energy systems by investigating innovative methods for energy management and optimization.

## 5.3 Future Prospects

Possible future research directions in this emerging area can be summarized as follows:

- Addressing scalability issues and exploring the integration of these proposed approaches into existing energy market infrastructure to further enhance the efficiency, transparency, and sustainability of energy transactions.
- Exploring more technical drawbacks and impacts of DEXs on energy trading and investigating intra-VPP optimization through Heuristic Algorithms.
- Investigating the potential of using reinforcement learning or other more sophisticated learning techniques to adaptively optimize energy trading strategies in response to changing market conditions and the evolving behavior of VPPs and prosumers.
- Investigating the potential benefits of incorporating off-chain solutions or developing novel consensus mechanisms that can improve the scalability and security of P2P energy trading systems.

# BIBLIOGRAPHY


[1] IEA, “World Energy Outlook 2021,” 2021. Accessed: Feb. 17, 2022. [Online]. Available: https://www.iea.org/reports/world-energy-outlook-2021

[2] IEA, “World Energy Outlook 2022,” 2022. Accessed: Jan. 17, 2023. [Online]. Available: https://www.iea.org/reports/world-energy-outlook-2022

[3] IEA, “Global Energy Review 2021,” Paris, 2021. Accessed: Feb. 15, 2021. [Online]. Available: https://www.iea.org/reports/global-energy-review-2021

[4] International Renewable Energy Agency (IRENA), “World energy transitions outlook 2022,” 2022. Accessed: Jan. 17, 2023. [Online]. Available: https://irena.org/Digital-Report/World-Energy-Transitions-Outlook-2022

[5] IEA, “Energy Technology Perspectives 2023,” OECD, Jan. 2023. doi: 10.1787/7c6b23db-en.

[6] S. Seven, G. Yao, A. Soran, A. Onen, and S. M. Muyeen, “Peer-to-Peer Energy Trading in Virtual Power Plant Based on Blockchain Smart Contracts,” *IEEE Access*, vol. 8, pp. 175713–175726, 2020, doi: 10.1109/ACCESS.2020.3026180.

[7] S. Seven *et al.*, “Energy Trading on a Peer-to-Peer Basis between Virtual Power Plants Using Decentralized Finance Instruments,” *Sustainability (Switzerland)*, vol. 14, no. 20, Oct. 2022, doi: 10.3390/su142013286.

[8] X. Cao, J. Wang, and B. Zeng, “Distributed Generation Planning Guidance Through Feasibility and Profit Analysis,” *IEEE Trans Smart Grid*, vol. 9, no. 5, pp. 5473–5475, 2018.

[9] A. Majzoobi and A. Khodaei, “Application of Microgrids in Supporting Distribution Grid Flexibility,” *IEEE Transactions on Power Systems*, vol. 32, no. 5, pp. 3660–3669, Sep. 2017.

[10] A. Khayatian, M. Barati, and G. J. Lim, “Integrated Microgrid Expansion Planning in Electricity Market With Uncertainty,” *IEEE Transactions on Power Systems*, vol. 33, no. 4, pp. 3634–3643, Jul. 2018, doi: 10.1109/TPWRS.2017.2768302.

[11] L. Yavuz, A. Önen, S. M. Muyeen, and I. Kamwa, “Transformation of microgrid to virtual power plant – a comprehensive review,” *IET Generation, Transmission & Distribution*, vol. 13, no. 11, pp. 1994–2005, Jun. 2019, doi: 10.1049/iet-gtd.2018.5649.

[12] C. Zhang, J. Wu, M. Cheng, Y. Zhou, and C. Long, “A Bidding System for Peer-to-Peer Energy Trading in a Grid-connected Microgrid,” *Energy Procedia*, vol. 103, pp. 147–152, Dec. 2016, doi: 10.1016/j.egypro.2016.11.264.

[13] W. Saad, Z. Han, H. Poor, and T. Basar, “Game-Theoretic Methods for the Smart Grid: An Overview of Microgrid Systems, Demand-Side Management, and Smart Grid Communications,” *IEEE Signal Process Mag*, vol. 29, no. 5, pp. 86–105, Sep. 2012.

[14] I. Atzeni, L. G. Ordonez, G. Scutari, D. P. Palomar, and J. R. Fonollosa, “Demand-Side Management via Distributed Energy Generation and Storage Optimization,” *IEEE Trans Smart Grid*, vol. 4, no. 2, pp. 866–876, Jun. 2013.

[15] Y. Wang, W. Saad, Z. Han, H. V. Poor, and T. Başar, “A Game-Theoretic Approach to Energy Trading in the Smart Grid,” *IEEE Trans Smart Grid*, vol. 5, no. 3, pp. 1439–1450, Oct. 2013.

[16] N. Zhang, Y. Yan, and W. Su, “A game-theoretic economic operation of residential distribution system with high participation of distributed electricity prosumers,” *Appl Energy*, vol. 154, pp. 471–479, Sep. 2015.

[17] W. Tushar, T. K. Saha, C. Yuen, P. Liddell, R. Bean, and H. V. Poor, "Peer-to-Peer Energy Trading With Sustainable User Participation: A Game Theoretic Approach," *IEEE Access*, vol. 6, pp. 62932–62943, 2018.
[18] W. Tushar *et al.*, "Grid Influenced Peer-to-Peer Energy Trading," *IEEE Trans Smart Grid*, vol. 11, no. 2, pp. 1407–1418, Mar. 2020.
[19] T. Morstyn, A. Teytelboym, and M. D. McCulloch, "Bilateral contract networks for peer-to-peer energy trading," *IEEE Trans Smart Grid*, vol. 10, no. 2, pp. 2026–2035, 2019, doi: 10.1109/TSG.2017.2786668.
[20] T. Morstyn, N. Farrell, S. J. Darby, and M. D. McCulloch, "Using peer-to-peer energy-trading platforms to incentivize prosumers to form federated power plants," *Nat Energy*, vol. 3, no. 2, pp. 94–101, 2018, doi: 10.1038/s41560-017-0075-y.
[21] M. F. Zia, E. Elbouchikhi, and M. Benbouzid, "Microgrids energy management systems: A critical review on methods, solutions, and prospects," *Appl Energy*, vol. 222, pp. 1033–1055, Jul. 2018.
[22] C. Zhang, J. Wu, C. Long, and M. Cheng, "Review of Existing Peer-to-Peer Energy Trading Projects," *Energy Procedia*, vol. 105, pp. 2563–2568, May 2017.
[23] "Research Project Smart Watts." [Online]. Available: https://www.psi-energymarkets.de/en/company/research-and-development/smart-watts/
[24] "vandebron." [Online]. Available: https://vandebron.nl
[25] "SmartWatt energy solutions." [Online]. Available: www.smartwatt.com
[26] "Smartwatt Solutions for Energy Systems." [Online]. Available: https://smartwatt.pt
[27] B. Brandherm, J. Baus, and J. Frey, "Peer Energy Cloud -- Civil Marketplace for Trading Renewable Energies," in *2012 Eighth International Conference on Intelligent Environments*, IEEE, Jun. 2012, pp. 375–378.
[28] "Electron." [Online]. Available: https://www.electron.org.uk
[29] L. Energy, "The USA's first consumer energy transaction begins 'power to the people' revolution in New York." [Online]. Available: https://lo3energy.com/usas-first-consumer-energy-transaction-begins-power-people-revolution-new-york/
[30] E. Mengelkamp, J. Gärttner, K. Rock, S. Kessler, L. Orsini, and C. Weinhardt, "Designing microgrid energy markets," *Appl Energy*, vol. 210, pp. 870–880, Apr. 2018, doi: 10.1016/j.apenergy.2017.06.054.
[31] "White Gum Valley energy sharing." [Online]. Available: https://westernpower.com.au/energy-solutions/projects-and-trials/white-gum-valley-energy-sharing/
[32] "Power Ledger." [Online]. Available: https://www.powerledger.io
[33] M. Andoni *et al.*, "Blockchain technology in the energy sector: A systematic review of challenges and opportunities," *Renewable and Sustainable Energy Reviews*, vol. 100, pp. 143–174, Feb. 2019.
[34] J. Kang, R. Yu, X. Huang, S. Maharjan, Y. Zhang, and E. Hossain, "Enabling Localized Peer-to-Peer Electricity Trading Among Plug-in Hybrid Electric Vehicles Using Consortium Blockchains," *IEEE Trans Industr Inform*, vol. 13, no. 6, pp. 3154–3164, Dec. 2017.
[35] X. Huang, C. Xu, P. Wang, and H. Liu, "LNSC: A Security Model for Electric Vehicle and Charging Pile Management Based on Blockchain Ecosystem," *IEEE Access*, vol. 6, pp. 13565–13574, 2018.
[36] N. Z. Aitzhan and D. Svetinovic, "Security and Privacy in Decentralized Energy Trading Through Multi-Signatures, Blockchain and Anonymous Messaging Streams," *IEEE Trans Dependable Secure Comput*, vol. 15, no. 5, pp. 840–852, Sep. 2018.

[37] Z. Li, J. Kang, R. Yu, D. Ye, Q. Deng, and Y. Zhang, "Consortium blockchain for secure energy trading in industrial internet of things," *IEEE Trans Industr Inform*, vol. 14, no. 8, pp. 3690–3700, 2018, doi: 10.1109/TII.2017.2786307.

[38] E. Mengelkamp, B. Notheisen, C. Beer, D. Dauer, and C. Weinhardt, "A blockchain-based smart grid: towards sustainable local energy markets," *Computer Science - Research and Development*, vol. 33, no. 1–2, pp. 207–214, Feb. 2018.

[39] K. Gai, Y. Wu, L. Zhu, M. Qiu, and M. Shen, "Privacy-Preserving Energy Trading Using Consortium Blockchain in Smart Grid," *IEEE Trans Industr Inform*, vol. 15, no. 6, pp. 3548–3558, Jun. 2019.

[40] S. Wang, A. F. Taha, J. Wang, K. Kvaternik, and A. Hahn, "Energy Crowdsourcing and Peer-to-Peer Energy Trading in Blockchain-Enabled Smart Grids," *IEEE Trans Syst Man Cybern Syst*, vol. 49, no. 8, pp. 1612–1623, Aug. 2019, doi: 10.1109/TSMC.2019.2916565.

[41] E. M. Radi, N. Lasla, S. Bakiras, and M. Mahmoud, "Privacy-Preserving Electric Vehicle Charging for Peer-to-Peer Energy Trading Ecosystems," in *ICC 2019 - 2019 IEEE International Conference on Communications (ICC)*, IEEE, May 2019, pp. 1–6.

[42] H. Liu, Y. Zhang, S. Zheng, and Y. Li, "Electric Vehicle Power Trading Mechanism Based on Blockchain and Smart Contract in V2G Network," *IEEE Access*, vol. 7, pp. 160546–160558, 2019.

[43] M. L. Di Silvestre *et al.*, "Ancillary Services in the Energy Blockchain for Microgrids," *IEEE Trans Ind Appl*, vol. 55, no. 6, pp. 7310–7319, 2019, doi: 10.1109/TIA.2019.2909496.

[44] M. Li, D. Hu, C. Lal, M. Conti, and Z. Zhang, "Blockchain-Enabled Secure Energy Trading With Verifiable Fairness in Industrial Internet of Things," *IEEE Trans Industr Inform*, vol. 16, no. 10, pp. 6564–6574, 2020, doi: 10.1109/TII.2020.2974537.

[45] R. Khalid, N. Javaid, A. Almogren, M. U. Javed, S. Javaid, and M. Zuair, "A Blockchain-Based Load Balancing in Decentralized Hybrid P2P Energy Trading Market in Smart Grid," *IEEE Access*, vol. 8, pp. 47047–47062, 2020, doi: 10.1109/ACCESS.2020.2979051.

[46] D. Han, C. Zhang, J. Ping, and Z. Yan, "Smart contract architecture for decentralized energy trading and management based on blockchains," *Energy*, vol. 199, p. 117417, 2020, doi: 10.1016/j.energy.2020.117417.

[47] N. Lasla, M. Al-Ammari, M. Abdallah, and M. Younis, "Blockchain Based Trading Platform for Electric Vehicle Charging in Smart Cities," *IEEE Open Journal of Intelligent Transportation Systems*, vol. 1, pp. 80–92, 2020.

[48] C. Burger, A. Kuhlmann, P. Richard, and J. Weinmann, "Blockchain in the energy transition. A survey among decision-makers in the German energy industry," *DENA German Energy Agency*, p. 41, 2016.

[49] S. Nakamoto, "Bitcoin: A Peer-to-Peer Electronic Cash System," *www.bitcoin.org*, 2008, doi: 10.1007/s10838-008-9062-0.

[50] A. S. Musleh, G. Yao, and S. M. Muyeen, "Blockchain Applications in Smart Grid–Review and Frameworks," *IEEE Access*, vol. 7, pp. 86746–86757, 2019, doi: 10.1109/ACCESS.2019.2920682.

[51] K. Christidis and M. Devetsikiotis, "Blockchains and Smart Contracts for the Internet of Things," *IEEE Access*, vol. 4, pp. 2292–2303, 2016, doi: 10.1109/ACCESS.2016.2566339.

[52] M. Mukhopadhyay, *Ethereum Smart Contract Development*. Packt, 2018.

[53] Ethereum Foundation, “Ethereum Project.” [Online]. Available: https://www.ethereum.org
[54] N. Szabo, “Formalizing and Securing Relationships on Public Networks,” *First Monday*, vol. 2, no. 9, 1997, doi: 10.5210/fm.v2i9.548.
[55] E. Foundation, “Remix Ethereum Browser IDE.” 2018. [Online]. Available: https://remix.readthedocs.io/en/latest/
[56] E. Community, “TestNet Ropsten (ETH) Blockchain Explorer.” 2019. [Online]. Available: https://ropsten.etherscan.io
[57] L. Koçkesen and E. A. Ok, “Auctions,” *An Introduction to Game Theory*. Koç University, Newyork University, pp. 117–124, 2007. [Online]. Available: http://home.ku.edu.tr/lkockesen/public_html/teaching/econ333/lectnotes/uggame.pdf
[58] C.-C. Chang, T.-F. Cheng, and W.-Y. Chen, “A Novel Electronic English Auction System With a Secure On-Shelf Mechanism,” *IEEE Transactions on Information Forensics and Security*, vol. 8, no. 4, pp. 657–668, 2013, doi: 10.1109/TIFS.2013.2250431.
[59] E. Foundation, “Common Patterns, Withdrawal from Contracts,” no. Mm. 2019. [Online]. Available: https://solidity.readthedocs.io/en/v0.5.9/common-patterns.html
[60] C. Liu, K. K. Chai, X. Zhang, E. T. Lau, and Y. Chen, “Adaptive Blockchain-Based Electric Vehicle Participation Scheme in Smart Grid Platform,” *IEEE Access*, vol. 6, pp. 25657–25665, 2018, doi: 10.1109/ACCESS.2018.2835309.
[61] L. Bader, J. C. Burger, R. Matzutt, and K. Wehrle, “Smart Contract-Based Car Insurance Policies,” *2018 IEEE Globecom Workshops, GC Wkshps 2018 - Proceedings*, 2019, doi: 10.1109/GLOCOMW.2018.8644136.
[62] H. Desai, M. Kantarcioglu, and L. Kagal, “A Hybrid Blockchain Architecture for Privacy-Enabled and Accountable Auctions,” in *2019 IEEE International Conference on Blockchain (Blockchain)*, IEEE, 2019, pp. 34–43. doi: 10.1109/Blockchain.2019.00014.
[63] X. Zhao, Z. Chen, X. Chen, Y. Wang, and C. Tang, “The DAO attack paradoxes in propositional logic,” in *2017 4th International Conference on Systems and Informatics (ICSAI)*, IEEE, 2017, pp. 1743–1746. doi: 10.1109/ICSAI.2017.8248566.
[64] N. Y. Lee, J. Yang, M. M. H. Onik, and C. S. Kim, “Modifiable Public Blockchains Using Truncated Hashing and Sidechains,” *IEEE Access*, vol. 7, pp. 173571–173582, 2019, doi: 10.1109/ACCESS.2019.2956628.
[65] R. Tso, Z. Y. Liu, and J. H. Hsiao, “Distributed E-voting and E-bidding systems based on smart contract,” *Electronics (Switzerland)*, vol. 8, no. 4, pp. 1–22, 2019, doi: 10.3390/electronics8040422.
[66] H. S. Galal and A. M. Youssef, “Verifiable Sealed-Bid Auction on the Ethereum Blockchain,” *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 10958 LNCS. pp. 265–278, 2019. doi: 10.1007/978-3-662-58820-8_18.
[67] P. Zheng, Z. Zheng, X. Luo, X. Chen, and X. Liu, “A detailed and real-time performance monitoring framework for blockchain systems,” in *Proceedings of the 40th International Conference on Software Engineering Software Engineering in Practice - ICSE-SEIP ’18*, ACM Press, 2018, pp. 134–143. doi: 10.1145/3183519.3183546.

[68] R. Khan *et al.*, “Energy Sustainability–Survey on Technology and Control of Microgrid, Smart Grid and Virtual Power Plant,” *IEEE Access*, vol. 9, pp. 104663–104694, 2021, doi: 10.1109/ACCESS.2021.3099941.
[69] Y. Yoldaş, A. Önen, S. M. Muyeen, A. V. Vasilakos, and İ. Alan, “Enhancing smart grid with microgrids: Challenges and opportunities,” *Renewable and Sustainable Energy Reviews*, vol. 72, pp. 205–214, May 2017, doi: 10.1016/j.rser.2017.01.064.
[70] B. Goia, T. Cioara, and I. Anghel, “Virtual Power Plant Optimization in Smart Grids: A Narrative Review,” *Future Internet*, vol. 14, no. 5, p. 128, Apr. 2022, doi: 10.3390/fi14050128.
[71] A. Yagmur, B. A. Dedeturk, A. Soran, J. Jung, and A. Onen, “Blockchain-Based Energy Applications: The DSO Perspective,” *IEEE Access*, vol. 9, pp. 145605–145625, 2021, doi: 10.1109/ACCESS.2021.3122987.
[72] E. A. Bhuiyan, Md. Z. Hossain, S. M. Muyeen, S. R. Fahim, S. K. Sarker, and S. K. Das, “Towards next generation virtual power plant: Technology review and frameworks,” *Renewable and Sustainable Energy Reviews*, vol. 150, p. 111358, Oct. 2021, doi: 10.1016/j.rser.2021.111358.
[73] M. Gržanić, T. Capuder, N. Zhang, and W. Huang, “Prosumers as active market participants: A systematic review of evolution of opportunities, models and challenges,” *Renewable and Sustainable Energy Reviews*, vol. 154, no. November 2021, p. 111859, Feb. 2022, doi: 10.1016/j.rser.2021.111859.
[74] T. Pinto, Z. Vale, and S. Widergren, *Local Electricity Markets*. Academic Press, 2021.
[75] K. Anoh, S. Maharjan, A. Ikpehai, Y. Zhang, and B. Adebisi, “Energy Peer-to-Peer Trading in Virtual Microgrids in Smart Grids: A Game-Theoretic Approach,” *IEEE Trans Smart Grid*, vol. 11, no. 2, pp. 1264–1275, 2020, doi: 10.1109/TSG.2019.2934830.
[76] L. Ali, S. M. Muyeen, H. Bizhani, and A. Ghosh, “A peer-to-peer energy trading for a clustered microgrid – Game theoretical approach,” *International Journal of Electrical Power & Energy Systems*, vol. 133, p. 107307, Dec. 2021, doi: 10.1016/j.ijepes.2021.107307.
[77] L. Ali, S. M. Muyeen, H. Bizhani, and A. Ghosh, “A multi-objective optimization for planning of networked microgrid using a game theory for peer-to-peer energy trading scheme,” *IET Generation, Transmission & Distribution*, vol. 15, no. 24, pp. 3423–3434, Dec. 2021, doi: 10.1049/gtd2.12308.
[78] G. Belgioioso, W. Ananduta, S. Grammatico, and C. Ocampo-Martinez, “Operationally-Safe Peer-to-Peer Energy Trading in Distribution Grids: A Game-Theoretic Market-Clearing Mechanism,” *IEEE Trans Smart Grid*, vol. 13, no. 4, pp. 2897–2907, Jul. 2022, doi: 10.1109/TSG.2022.3158442.
[79] L. Wang, Y. Zhang, W. Song, and Q. Li, “Stochastic Cooperative Bidding Strategy for Multiple Microgrids With Peer-to-Peer Energy Trading; Stochastic Cooperative Bidding Strategy for Multiple Microgrids With Peer-to-Peer Energy Trading,” *IEEE Trans Industr Inform*, vol. 18, no. 3, 2022, doi: 10.1109/TII.2021.3094274.
[80] W. Tushar, T. K. Saha, C. Yuen, D. Smith, and H. V. Poor, “Peer-to-Peer Trading in Electricity Networks: An Overview,” *IEEE Trans Smart Grid*, vol. 11, no. 4, pp. 3185–3200, Jul. 2020, doi: 10.1109/TSG.2020.2969657.
[81] L. Gomes, Z. A. Vale, and J. M. Corchado, “Multi-Agent Microgrid Management System for Single-Board Computers: A Case Study on Peer-to-Peer Energy

Trading," *IEEE Access*, vol. 8, pp. 64169–64183, 2020, doi: 10.1109/ACCESS.2020.2985254.
[82] Z. Zhao, C. Feng, and A. L. Liu, "Comparisons of Auction Designs through Multi-Agent Learning in Peer-to-Peer Energy Trading," *IEEE Trans Smart Grid*, vol. 14, no. 1, pp. 1–13, Oct. 2022, doi: 10.1109/TSG.2022.3190814.
[83] J. S. Pankiraj, A. Yassine, and S. Choudhury, "Double-Sided Auction Mechanism for Peer-to-Peer Energy Trading Markets," in *2021 IEEE International Conference on Progress in Informatics and Computing (PIC)*, IEEE, Dec. 2021, pp. 443–452. doi: 10.1109/PIC53636.2021.9687026.
[84] H. Zhu, K. Ouahada, and A. M. Abu-Mahfouz, "Peer-to-Peer Energy Trading in Smart Energy Communities: A Lyapunov-Based Energy Control and Trading System," *IEEE Access*, vol. 10, pp. 42916–42932, 2022, doi: 10.1109/ACCESS.2022.3167828.
[85] L. A. Soriano, M. Avila, P. Ponce, J. de Jesús Rubio, and A. Molina, "Peer-to-peer energy trades based on multi-objective optimization," *International Journal of Electrical Power & Energy Systems*, vol. 131, no. March, p. 107017, Oct. 2021, doi: 10.1016/j.ijepes.2021.107017.
[86] A. Kochupurackal, K. P. Pancholi, S. N. Islam, A. Anwar, and A. M. T. Oo, "Rolling horizon optimisation based peer-to-peer energy trading under real-time variations in demand and generation," *Energy Systems*, pp. 1–25, May 2022, doi: 10.1007/s12667-022-00511-w.
[87] S. Cao, H. Zhang, K. Cao, M. Chen, Y. Wu, and S. Zhou, "Day-Ahead Economic Optimal Dispatch of Microgrid Cluster Considering Shared Energy Storage System and P2P Transaction," *Front Energy Res*, vol. 9, no. April, 2021, doi: 10.3389/fenrg.2021.645017.
[88] B. Zheng, Y. Fan, W. Wei, Y. Xu, S. Huang, and S. Mei, "Distribution Optimal Power Flow With Energy Sharing Via a Peer-To-Peer Transactive Market," *Front Energy Res*, vol. 9, no. July, pp. 1–14, Jul. 2021, doi: 10.3389/fenrg.2021.701149.
[89] D. S. Zha, T. T. Feng, X. L. Gong, and S. Y. Liu, "When energy meets blockchain: A systematic exposition of policies, research hotspots, applications, and prospects," *Int J Energy Res*, no. July, pp. 1–31, 2021, doi: 10.1002/er.7398.
[90] Y. Wu, Y. Wu, H. Cimen, J. C. Vasquez, and J. M. Guerrero, "P2P energy trading: Blockchain-enabled P2P energy society with multi-scale flexibility services," *Energy Reports*, vol. 8, pp. 3614–3628, Nov. 2022, doi: 10.1016/j.egyr.2022.02.074.
[91] M. I. Azim, W. Tushar, T. K. Saha, C. Yuen, and D. Smith, "Peer-to-peer kilowatt and negawatt trading: A review of challenges and recent advances in distribution networks," *Renewable and Sustainable Energy Reviews*, vol. 169, p. 112908, Nov. 2022, doi: 10.1016/j.rser.2022.112908.
[92] B. Li, F. Yang, B. Qi, X. F. Bai, Y. Sun, and S. Chen, "Research on key technologies of P2P transaction in virtual power plant based on blockchain," *IET Smart Grid*, vol. 5, no. 4, pp. 223–233, 2022, doi: 10.1049/stg2.12064.
[93] S. Cantillo-Luna, R. Moreno-Chuquen, H. R. Chamorro, V. K. Sood, S. Badsha, and C. Konstantinou, "Blockchain for Distributed Energy Resources Management and Integration," *IEEE Access*, vol. 10, no. May, pp. 68598–68617, 2022, doi: 10.1109/ACCESS.2022.3184704.
[94] A. Nadeem, "A survey on peer-to-peer energy trading for local communities: Challenges, applications, and enabling technologies," *Front Comput Sci*, vol. 4, p. 1008504, Sep. 2022, doi: 10.3389/fcomp.2022.1008504.

[95] T. Al-Abri *et al.*, “Review on Energy Application Using Blockchain Technology With an Introductions in the Pricing Infrastructure,” *IEEE Access*, vol. 10, no. July, pp. 80119–80137, 2022, doi: 10.1109/ACCESS.2022.3194161.
[96] H. Javed *et al.*, “Recent Trends, Challenges, and Future Aspects of P2P Energy Trading Platforms in Electrical-Based Networks Considering Blockchain Technology: A Roadmap Toward Environmental Sustainability,” *Front Energy Res*, vol. 10, no. March, pp. 1–20, Mar. 2022, doi: 10.3389/fenrg.2022.810395.
[97] M. U. Hassan, M. H. Rehmani, and J. Chen, “Optimizing Blockchain Based Smart Grid Auctions: A Green Revolution,” *IEEE Transactions on Green Communications and Networking*, vol. 6, no. 1, pp. 462–471, Mar. 2022, doi: 10.1109/TGCN.2021.3095424.
[98] S. N. Gourisetti *et al.*, “Blockchain Smart Contracts for Transactive Energy Systems,” Richland, WA (United States), Aug. 2019. doi: 10.2172/1658380.
[99] T. AlSkaif, J. L. Crespo-Vazquez, M. Sekuloski, G. van Leeuwen, and J. P. S. Catalao, “Blockchain-Based Fully Peer-to-Peer Energy Trading Strategies for Residential Energy Systems,” *IEEE Trans Industr Inform*, vol. 18, no. 1, pp. 231–241, Jan. 2022, doi: 10.1109/TII.2021.3077008.
[100] G. Vieira and J. Zhang, “Peer-to-peer energy trading in a microgrid leveraged by smart contracts,” *Renewable and Sustainable Energy Reviews*, vol. 143, no. February, p. 110900, Jun. 2021, doi: 10.1016/j.rser.2021.110900.
[101] M. Gough *et al.*, “Blockchain-Based Transactive Energy Framework for Connected Virtual Power Plants,” *IEEE Trans Ind Appl*, vol. 58, no. 1, pp. 986–995, Jan. 2022, doi: 10.1109/TIA.2021.3131537.
[102] S. Eisele, A. Laszka, D. C. Schmidt, and A. Dubey, “The Role of Blockchains in Multi-Stakeholder Transactive Energy Systems,” *Frontiers in Blockchain*, vol. 3, no. December, pp. 1–18, Dec. 2020, doi: 10.3389/fbloc.2020.593471.
[103] T. Cioara, M. Antal, V. T. Mihailescu, C. D. Antal, I. M. Anghel, and D. Mitrea, “Blockchain-Based Decentralized Virtual Power Plants of Small Prosumers,” *IEEE Access*, vol. 9, pp. 29490–29504, 2021, doi: 10.1109/ACCESS.2021.3059106.
[104] Y. Wu, J. Li, and J. Gao, “Real-Time Bidding Model of Cryptocurrency Energy Trading Platform,” *Energies (Basel)*, vol. 14, no. 21, p. 7216, Nov. 2021, doi: 10.3390/en14217216.
[105] S. N. G. Gourisetti *et al.*, “Blockchain smart contract reference framework and program logic architecture for transactive energy systems,” *Appl Energy*, vol. 304, no. September, p. 117860, Dec. 2021, doi: 10.1016/j.apenergy.2021.117860.
[106] Y. Huang, Y. Bian, R. Li, J. L. Zhao, and P. Shi, “Smart Contract Security: A Software Lifecycle Perspective,” *IEEE Access*, vol. 7, pp. 150184–150202, 2019, doi: 10.1109/ACCESS.2019.2946988.
[107] S. Sayeed, H. Marco-Gisbert, and T. Caira, “Smart Contract: Attacks and Protections,” *IEEE Access*, vol. 8, pp. 24416–24427, 2020, doi: 10.1109/ACCESS.2020.2970495.
[108] Z. Wan, X. Xia, D. Lo, J. Chen, X. Luo, and X. Yang, “Smart Contract Security: A Practitioners’ Perspective,” in *2021 IEEE/ACM 43rd International Conference on Software Engineering (ICSE)*, IEEE, May 2021, pp. 1410–1422. doi: 10.1109/ICSE43902.2021.00127.
[109] U. Cali *et al.*, “Standardization of Smart Contracts for Energy Markets and Operation,” in *2022 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, IEEE, Apr. 2022, pp. 1–5. doi: 10.1109/ISGT50606.2022.9817542.

[110] V. V. Buterin, “A Next Generation Smart Contract & Decentralized Application Platform,” 2014. Accessed: Apr. 14, 2023. [Online]. Available: https://ethereum.org/669c9e2e2027310b6b3cdce6e1c52962/Ethereum_Whitepaper_-_Buterin_2014.pdf

[111] W. Cai, Z. Wang, J. B. Ernst, Z. Hong, C. Feng, and V. C. M. Leung, “Decentralized Applications: The Blockchain-Empowered Software System,” *IEEE Access*, vol. 6, pp. 53019–53033, Oct. 2018, doi: 10.1109/ACCESS.2018.2870644.

[112] W. Metcalfe, “Ethereum, Smart Contracts, DApps,” in *Blockchain and Crypto Currency: Building a High Quality Marketplace for Crypto Data*, M. Yano, C. Dai, K. Masuda, and Y. Kishimoto, Eds., in Economics, Law, and Institutions in Asia Pacific. Singapore: Springer, 2020, pp. 77–93. doi: 10.1007/978-981-15-3376-1_5.

[113] K. Qin and A. Gervais, “An overview of blockchain scalability, interoperability and sustainability,” *Hochschule Luzern Blockchain Lab*, p. 15, 2018, [Online]. Available: https://www.eublockchainforum.eu/sites/default/files/research-paper/an_overview_of_blockchain_scalability_interoperability_and_sustainability.pdf

[114] P. Wallace, “Layer 1 vs Layer 2 : What you need to know about different Blockchain Layer solutions,” *The Capital | Medium*, 2020. https://medium.com/the-capital/layer-1-vs-layer-2-what-you-need-to-know-about-different-blockchain-layer-solutions-69f91904ce40 (accessed Feb. 06, 2022).

[115] B. Berkowitz, “What Is Ethereum 2.0 and When Will It Happen?,” *The Motley Fool*, 2021. https://www.fool.com/investing/2021/05/27/what-is-ethereum-20-and-when-will-it-happen/ (accessed Feb. 06, 2022).

[116] K. Sekniqi, D. Laine, S. Buttolph, and E. G. Sirer, “Avalanche Platform,” 2020. Accessed: Apr. 14, 2023. [Online]. Available: https://assets.website-files.com/5d80307810123f5ffbb34d6e/6008d7bbf8b10d1eb01e7e16_Avalanche%20Platform%20Whitepaper.pdf

[117] R. Tsepeleva and V. Korkhov, “Building DeFi Applications Using Cross-Blockchain Interaction on the Wish Swap Platform,” *Computers*, vol. 11, no. 6, p. 99, Jun. 2022, doi: 10.3390/computers11060099.

[118] Ethereum Foundation, “Decentralized finance (DeFi) | ethereum.org,” 2021. https://ethereum.org/en/defi/ (accessed May 19, 2022).

[119] Pangolin, “GitHub - pangolindex/exchange-contracts,” 2021.

[120] OpenZeppelin, “openzeppelin-contracts/ERC20PresetMinterPauser.sol at master · OpenZeppelin/openzeppelin-contracts · GitHub,” 2020. https://github.com/OpenZeppelin/openzeppelin-contracts/blob/master/contracts/token/ERC20/presets/ERC20PresetMinterPauser.sol (accessed Feb. 23, 2022).

[121] J. Kulpa, P. Olczak, K. Stecuła, and M. Sołtysik, “The Impact of RES Development in Poland on the Change of the Energy Generation Profile and Reduction of CO2 Emissions,” *Applied Sciences*, vol. 12, no. 21, p. 11064, Nov. 2022, doi: 10.3390/app122111064.

[122] O. Korkmaz and B. Önöz, “Modelling the Potential Impacts of Nuclear Energy and Renewables in the Turkish Energy System,” *Energies (Basel)*, vol. 15, no. 4, p. 1392, Feb. 2022, doi: 10.3390/en15041392.

[123] J. Kong, S. Oh, B. O. Kang, and J. Jung, "Development of an incentive model for renewable energy resources using forecasting accuracy in South Korea," *Energy Sci Eng*, vol. 10, no. 9, pp. 3250–3266, Sep. 2022, doi: 10.1002/ese3.1020.
[124] M. Villa-Arrieta and A. Sumper, "Economic evaluation of Nearly Zero Energy Cities," *Appl Energy*, vol. 237, pp. 404–416, Mar. 2019, doi: 10.1016/j.apenergy.2018.12.082.
[125] V. Krakowski, E. Assoumou, V. Mazauric, and N. Maïzi, "Feasible path toward 40–100% renewable energy shares for power supply in France by 2050: A prospective analysis," *Appl Energy*, vol. 171, pp. 501–522, Jun. 2016, doi: 10.1016/j.apenergy.2016.03.094.
[126] M. S. Symiakakis and F. D. Kanellos, "Towards the detailed modeling of deregulated electricity markets comprising Smart prosumers and peer to peer energy trading," *Electric Power Systems Research*, vol. 217, no. December 2022, p. 109158, Apr. 2023, doi: 10.1016/j.epsr.2023.109158.
[127] S. Thangavel, D. Mohanraj, T. Girijaprasanna, S. Raju, C. Dhanamjayulu, and S. M. Muyeen, "A Comprehensive Review on Electric Vehicle: Battery Management System, Charging Station, Traction Motors," *IEEE Access*, vol. 11, pp. 20994–21019, 2023, doi: 10.1109/ACCESS.2023.3250221.
[128] S. S. Ravi and M. Aziz, "Utilization of Electric Vehicles for Vehicle-to-Grid Services: Progress and Perspectives," *Energies (Basel)*, vol. 15, no. 2, p. 589, Jan. 2022, doi: 10.3390/en15020589.
[129] M. Khemir, M. Rojas, R. Popova, T. Feizi, J. F. Heinekamp, and K. Strunz, "Real-World Application of Sustainable Mobility in Urban Microgrids," *IEEE Trans Ind Appl*, vol. 58, no. 2, pp. 1396–1405, Mar. 2022, doi: 10.1109/TIA.2021.3132847.
[130] A. Maheshwari, M. Heleno, and M. Ludkovski, "The effect of rate design on power distribution reliability considering adoption of distributed energy resources," *Appl Energy*, vol. 268, p. 114964, Jun. 2020, doi: 10.1016/j.apenergy.2020.114964.
[131] E. Galvan, P. Mandal, and Y. Sang, "Networked microgrids with roof-top solar PV and battery energy storage to improve distribution grids resilience to natural disasters," *International Journal of Electrical Power & Energy Systems*, vol. 123, p. 106239, Dec. 2020, doi: 10.1016/j.ijepes.2020.106239.
[132] M. Bertolini, C. D'Alpaos, and M. Moretto, "Do Smart Grids boost investments in domestic PV plants? Evidence from the Italian electricity market," *Energy*, vol. 149, pp. 890–902, Apr. 2018, doi: 10.1016/j.energy.2018.02.038.
[133] F. Bandeiras, Á. Gomes, M. Gomes, and P. Coelho, "Exploring Energy Trading Markets in Smart Grid and Microgrid Systems and Their Implications for Sustainability in Smart Cities," *Energies (Basel)*, vol. 16, no. 2, p. 801, Jan. 2023, doi: 10.3390/en16020801.
[134] L. Ali *et al.*, "Blockchain-Based Local Energy Market Enabling P2P Trading: An Australian Collated Case Study on Energy Users, Retailers and Utilities," *IEEE Access*, vol. 10, no. December, pp. 124429–124447, 2022, doi: 10.1109/ACCESS.2022.3224936.
[135] M. R. Alam, M. St-Hilaire, and T. Kunz, "Peer-to-peer energy trading among smart homes," *Appl Energy*, vol. 238, no. January, pp. 1434–1443, 2019, doi: 10.1016/j.apenergy.2019.01.091.
[136] M. Yan, M. Shahidehpour, A. Paaso, L. Zhang, A. Alabdulwahab, and A. Abusorrah, "Distribution Network-Constrained Optimization of Peer-to-Peer Transactive Energy Trading among Multi-Microgrids," *IEEE Trans Smart Grid*, vol. 12, no. 2, pp. 1033–1047, 2021, doi: 10.1109/TSG.2020.3032889.

[137] H. Huang, S. Nie, J. Lin, Y. Wang, and J. Dong, "Optimization of peer-to-peer power trading in a microgrid with distributed PV and battery energy storage systems," *Sustainability (Switzerland)*, vol. 12, no. 3, 2020, doi: 10.3390/su12030923.

[138] J. D. Warner and T. M. Masaud, "Decentralized Peer-to-Peer Energy Trading Model for Networked Microgrids," *2021 IEEE Conference on Technologies for Sustainability, SusTech 2021*, pp. 7–12, 2021, doi: 10.1109/SusTech51236.2021.9467466.

[139] A. Jiang, H. Yuan, and D. Li, "A two-stage optimization approach on the decisions for prosumers and consumers within a community in the Peer-to-peer energy sharing trading," *International Journal of Electrical Power and Energy Systems*, vol. 125, no. September 2020, p. 106527, 2021, doi: 10.1016/j.ijepes.2020.106527.

[140] H. Zhang, S. Zhang, X. Hu, H. Cheng, Q. Gu, and M. Du, "Parametric optimization-based peer-to-peer energy trading among commercial buildings considering multiple energy conversion," *Appl Energy*, vol. 306, no. PB, p. 118040, 2022, doi: 10.1016/j.apenergy.2021.118040.

[141] L. Ali, S. M. Muyeen, H. Bizhani, and M. G. Simoes, "Economic Planning and Comparative Analysis of Market-Driven Multi-Microgrid System for Peer-to-Peer Energy Trading," *IEEE Trans Ind Appl*, vol. 58, no. 3, pp. 4025–4036, May 2022, doi: 10.1109/TIA.2022.3152140.

[142] T. D. Hutty, A. Pena-Bello, S. Dong, D. Parra, R. Rothman, and S. Brown, "Peer-to-peer electricity trading as an enabler of increased PV and EV ownership," *Energy Convers Manag*, vol. 245, p. 114634, Oct. 2021, doi: 10.1016/j.enconman.2021.114634.

[143] J. Liu, H. Yang, and Y. Zhou, "Peer-to-peer trading optimizations on net-zero energy communities with energy storage of hydrogen and battery vehicles," *Appl Energy*, vol. 302, no. August, p. 117578, 2021, doi: 10.1016/j.apenergy.2021.117578.

[144] A. Al-Sorour, M. Fazeli, M. Monfared, and A. A. Fahmy, "Investigation of Electric Vehicles Contributions in an Optimized Peer-to-Peer Energy Trading System," *IEEE Access*, vol. 11, no. February, pp. 12489–12503, 2023, doi: 10.1109/ACCESS.2023.3242052.

[145] G. Angeris, H.-T. Kao, R. Chiang, C. Noyes, and T. Chitra, "An Analysis of Uniswap markets," *Cryptoeconomic Systems*, vol. 0, no. 1, Nov. 2020, doi: 10.21428/58320208.c9738e64.

[146] "Litepapers - Pangolin DEX." https://docs.pangolin.exchange/intro/litepapers (accessed Feb. 26, 2023).

[147] "Projects – COIN-OR: Computational Infrastructure for Operations Research." https://www.coin-or.org/projects/ (accessed Mar. 10, 2023).

[148] "Optimization with PuLP — PuLP 2.7.0 documentation." https://coin-or.github.io/pulp/ (accessed Mar. 10, 2023).

# CURRICULUM VITAE

| | |
|---|---|
| 2005 – 2009 | B.Sc., Computer Engineering,<br>Kocaeli University, Kocaeli, TURKEY |
| 2012 – 2013 | M.Sc., Software Engineering,<br>Queen Mary University of London, London, UNITED KINGDOM |
| 2014 – 2023 | Ph.D., Electrical and Computer Engineering,<br>Abdullah Gül University, Kayseri, TURKEY |
| 2009 – 2010 | Computer Engineer, Lovely Professional University,<br>Jalandhar, INDIA |
| 2010 – 2011 | Assistant Software Engineer, Huawei Turkey R&D Center,<br>Istanbul, TURKEY |
| 2014 – Present | Research Assistant, Software Engineering Department,<br>Abdullah Gul University, Kayseri, TURKEY |

SELECTED PUBLICATIONS AND PRESENTATIONS

**J1)** S. Seven, G. Yao, A. Soran, A. Onen, and S. M. Muyeen, Peer-to-peer energy trading in virtual power plant based on blockchain smart contracts, published in IEEE Access, (Sep. 2020).

**J2)** S. Seven, Y. Yoldas, A. Soran, G. Yalcin Alkan, J Jung, T. S. Ustun, and A. Onen, Energy Trading on a Peer-to-Peer Basis between Virtual Power Plants Using Decentralized Finance Instruments, published in Sustainability (Oct. 2022).

**J3)** S. Seven, Y. Yoldas, G. Yalcin Alkan and A. Onen, Deep Learning to Optimize Peer-to-Peer Energy Trading via a Decentralized Exchange among Virtual Power Plants, under review.