# AUTONOMOUS AND DECENTRALISED ENERGY MARKETS IN SMART DC MICROGRIDS

by

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# SUMMARY

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| | |
|---|---|
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Microgrids are gaining popularity due to their ability to integrate distributed renewable energy generation. In addition, direct current (DC) - based operation results in significantly higher operational efficiency. However, it exhibits energy drawbacks such as congestion, instability, and imbalances. Incorporating demand management through electricity markets governed by dynamic pricing presents a potential solution to these challenges. Concerns about unfair electricity pricing and uneven market power hinder electricity market adoption. This research aims to facilitate decentralised and transparent energy markets with a high-accuracy dynamic pricing scheme to address the critical arguments against current electricity markets.

A two-part study is performed to achieve this aim. The first part of the study investigates a real-time dynamic pricing strategy to mitigate the risks of price volatility and market manipulation. The proposed scheme prioritises fair and efficient pricing by accounting for specialised factors at increased price space granularity. In addition, a complementary participant matching optimisation strategy is

explored to optimise transmission loss and congestion during the energy exchanges. The second part of the study develops a novel blockchain-based energy exchange platform. The platform is designed to autonomously coordinate and facilitate peer-to-peer (P2P) energy exchanges in a transparent, decentralised, secure and regulated environment.

A scientific approach is adopted throughout the study. A theoretical foundation is laid by comprehensively reviewing critical areas related to the field of research. The in-depth literature study examines electricity market configurations, pricing strategies, machine learning forecasting applications and blockchain technology. Shortcomings in the state-of-the-art are identified and considered when performing further research.

Systematic research is conducted due to the diverse nature of this research problem. The identified research gaps are bridged through experimentation. The findings from the research are then provided and critically analysed in this study. Finally, key findings and research areas of improvement are provided in the conclusion. The research performed in this dissertation entails investigating traditional electricity market approaches, comparing short-term energy forecasting methods through 42 different machine learning algorithms, optimising participant matching configurations in electricity markets, developing a real-time dynamic price strategy, exploring conventional smart contract solutions and developing a specialised P2P blockchain trading system for electricity markets.

The objective of this research has been achieved with the identified hypotheses accepted and the research questions answered. Thus, the study demonstrates a comprehensive approach to decentralised, transparent and regulated peer-to-peer energy exchanges countering arguments against the fairness of electricity markets. In doing so, the adoption rates of electricity markets can be improved whilst offering an incentive to increase localised renewable energy generation levels. The research further contributes to enhanced energy management, efficiency and resiliency in DC microgrids.

# LIST OF ABBREVIATIONS

| | |
|---|---|
| AC | alternating current |
| AI | artificial intelligence |
| ANFIS | adaptive neuro fuzzy inference system |
| ANN | artificial neural network |
| ARMA | auto regressive moving average |
| CPP | critical peak pricing |
| DC | direct current |
| DL | deep learning |
| ELM | extreme learning machine |
| ETR | extra trees regressor |
| GBRT | gradient boosted regression trees |
| GPR | gaussian process regression |
| HTTP | hypertext transfer protocol |
| IDE | integrated development environment |
| JSON | javascript object notation |
| KNN | k-nearest neighbour |
| LMP | locational marginal pricing |
| LP | linear program |
| LR | linear regression |
| MAE | mean absolute error |
| MAPE | mean absolute percent error |
| MCP | market clearing price |
| ML | machine learning |
| MLFFNN | multi-layer feed-forward neural network |
| MLP | multilayer perceptron |
| MSE | mean squared error |
| P2P | peer-to-peer |
| PoW | proof-of-work |
| PoS | proof-of-stake |

| | |
|---|---|
| PV | photovoltaic |
| SVM | support vector machine |
| SVML | support vector machine learning |
| SVR | support vector regression |
| TOU | time-of-use |
| RBF | radial basis function |
| RES | renewable energy sources |
| RFR | random forest regressor |
| RF | radio frequency |
| RT | real-time |
| URL | uniform resource locator |

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# CHAPTER 1 INTRODUCTION

## 1.1 PROBLEM STATEMENT

### 1.1.1 Context of the Problem

There is an ongoing energy crisis worldwide. It can be attributed to the rapid rate of population growth, escalating energy demands and the energy production dependence on fossil fuels [1]. The global reserves of these non-renewable energy sources are steadily depleting. In addition, fossil fuel usage releases harmful and dangerous greenhouse gases to the environment [2]. Research efforts focus on developing sustainable energy solutions with a particular emphasis on renewable energy integration [3].

The incorporation of microgrids can assist in overcoming the energy crisis [4]. Microgrids exhibit a concentrated focus on decentralised renewable energy production, which is typically in the form of solar and wind energy. They improve grid reliability, reduce transmission losses, enhance voltage support and improve power quality [5]. Microgrids further exhibit an ameliorated operating efficiency, financial suitability and carbon footprint [6]. Furthermore, DC-based microgrids are gaining investment due to the rapid development of power electronics [7]. This configuration offers the advantages of reduced initial capital requirements, higher operating efficiencies, insensitivity to disturbances from the utility, reduced number of controllers and simpler grid synchronisation [2].

Despite the significant advantages of DC microgrids, they are susceptible to voltage transients from generator switching, bidirectional power flow and energy congestion [5]. The overarching challenges in these microgrids can be identified as maintaining energy balance, stability and reliability [6]. Demand management presents a potential solution to these challenges [8]. Techniques presently developed are driven by energy resource optimisation, leading to overlooked financial and technological considerations. These factors reduce microgrids' appeal in modern applications [9]. However, dynamic tariffs offer the advantage of accounting for these factors [10]. In retail markets, the prevalent forms of tariff schemes are through block or flat rates. These schemes are inefficient as they inadequately reflect the costs associated with the generation, transmission and distribution of energy [11]. Another disadvantage of present schemes is the inability to account for the load profiles of consumers. These disadvantages can be countered by implementing day-ahead predictions [12]. Further technological development is required to effectively assist in determining real-time tariffs capable of accounting for these factors. Research efforts are being focused on modelling the conditions to simulate the method reliably [13].

Energy markets present an opportunity for real-time dynamic pricing [14]. They enable more feasible demand management as it will incentivise users to shift their load profiles to obtain energy savings [15]. However, two key arguments are presented against the approach. Firstly, the scheme may result in unfair electricity prices to energy consumers [16]. Secondly, traditional electricity market mechanisms are centralised with supplier-centric structures. These configurations result in no market power for end-users capable of trading their excess energy resources [17].

### 1.1.2 Research Gap

DC microgrids are subject to numerous drawbacks, with the maintenance of energy balance being a key challenge. Furthermore, the current microgrid infrastructure is monolithic, resulting in occasional energy congestion. The application of electricity markets presents a promising opportunity for countering these challenges by stimulating demand response and localised energy production. However, the risks of inequitable electricity market operation must be addressed.

## 1.2 RESEARCH OBJECTIVE AND QUESTIONS

This research aims to facilitate decentralised and transparent energy markets with a high-accuracy dynamic pricing scheme to address the critical arguments against current electricity markets. Thus, contributing to improved electricity market adoption rates.

The following research questions will be answered in this work:

- Can dynamic pricing effectively account for real-time energy conditions in a microgrid?
- Can an energy market be facilitated in a decentralised, transparent and secure environment?

## 1.3 APPROACH

### 1.3.1 Research Approach

The drawbacks of energy imbalance in microgrids can be countered by establishing more extensive involvement from smaller-scale energy producers. One approach may be incorporating localised energy markets between consumers, prosumers and producers. Whilst improving the resilience of the microgrid, this approach enables demand management through dynamic pricing. The concern of unfair electricity prices can be addressed by incorporating a specialised dynamic pricing strategy capable of accounting for real-time energy and market conditions. In addition, the increased number of energy providers and improved price space granularity will allow individuals to vary their load profiles according to their preferences without being subjected to generalised electricity prices. Furthermore, distributed market power among all participants can be promoted by decentralising the electricity market. Blockchain technology can be used to facilitate this peer-to-peer trading environment.

### 1.3.2 Research Hypotheses

Two hypotheses have been identified for this study which is as follows:

1. If the energy and market conditions within a microgrid are accounted for, then a real-time dynamic tariff can be achieved.
2. Blockchain technology can facilitate a decentralised, transparent and secure energy market.

### 1.3.3 Research Procedure

The derived hypotheses are examined through the following research process containing closely associated stages. Consequently, there may be overlapping between activities. The process described should be considered a recursive cycle instead of a rigid method.

#### 1.3.3.1 Research Design Preparation

Preparing the research design entails developing a logical plan to address the research problem and hypothesis, which requires in-depth literature reviews and consideration of data collection, analysis, and evaluation methods. The availability of resources such as time, equipment and software are also considered.

#### 1.3.3.2 Data Collection

This stage entails executing designed simulations or experimentation. Data is then gathered, processed and stored.

#### 1.3.3.3 Data Analysis

Raw data is categorised with the aid of data filtering before performing statistical inferences.

#### 1.3.3.4 Generalisations and Interpretation

The results from the data analysis are critically discussed before concluding. If the hypothesis is rejected, the process is repeated.

## 1.4 RESEARCH GOALS

1. Improve the adoption of electricity markets by proposing a real-time tariff scheme capable of accounting for factors such as energy generated, energy demand, energy losses, and market prices.
2. Enable peer-to-peer energy exchanges in a decentralised, transparent and secure environment through blockchain technology.

## 1.5 RESEARCH CONTRIBUTION

Implementing a novel dynamic pricing scheme can promote more accurate and reliable electricity prices. In addition, the real-time nature of the pricing strategy will unlock greater degrees of market flexibility and demand response. Furthermore, facilitating electricity markets through blockchain technology will evenly distribute market power by coordinating energy exchanges in a transparent, decentralised and regulated environment. The research also incentivises localised renewable energy penetration and enhanced energy system deregulation.

The research addresses the concerns of inequitable electricity market operation. As a result, the feasibility of these markets for energy and congestion management in DC microgrids can be improved. Despite DC microgrids being targeted in this research, the scheme can be adapted to other forms of power systems. It is envisioned that the integration of DC microgrids will be increased by overcoming the challenge of energy congestion and imbalances. This outcome will improve the system's resiliency, transparency and efficiency. As a result, the research will contribute to overcoming the worldwide energy crisis.

## 1.6 RESEARCH OUTPUTS

Aspects of the research performed have been presented at international scientific conferences and published in a combination of proceedings and textbooks. Details of the research outputs are as follows:

1. N. R. Naraindath, R. C. Bansal and R. M. Naidoo, "The Uprising of Blockchain Technology in the Energy Market Industry," in *International Conference on Recent Developments in Electrical and Electronics Engineering*, Faridabad, India, April 15-16, 2022.
2. N. R. Naraindath, R. C. Bansal and R. M. Naidoo, "Development of an Exploratory Blockchain for Enhanced Data Security in Smart Grids," in *International Conference on Artificial Intelligence Techniques for Electrical Engineering Systems*, Andhra Pradesh, India, May 6-7, 2022.
3. N. R. Naraindath, R. C. Bansal and R. M. Naidoo, "Investigating the Application of Ethereum Smart Contracts in Energy Exchanges," in *International Conference on Signals, Machines and Automation*, New Delhi, India, August 4-5, 2022.
4. N. R. Naraindath, R. M. Naidoo and R. C. Bansal, "Autonomous and Decentralised Energy Markets in DC Microgrids," in *International Conference on Green Energy and Environmental Technology*, Rome, Italy, July 27-29, 2022.
5. N. R. Naraindath, R. M. Naidoo and R. C. Bansal, "Autonomous and Decentralised Energy Markets in Smart DC Microgrids," *Applied Energy*, 2022 (work in progress).

## 1.7 OVERVIEW OF STUDY

This chapter introduces the research problem whilst briefly providing insight into the research approach. Chapter 2 describes the in-depth literature review of the state-of-the-art related to the research problem. Chapter 3 systematically presents the experimental methods and case studies considered in this research. Chapter 4 outlines the gathered results from the conducted experimentation. Chapter 5 then comprehensively analyses and evaluates the experimental results whilst identifying research limitations. Lastly, Chapter 6 provides concluding remarks from the study along with suggestions for further research.

# CHAPTER 2 LITERATURE STUDY

## 2.1 CHAPTER OVERVIEW

This chapter contains all literature reviewed for the diverse elements related to the study, which serves as the theoretical benchmark for the research scope. An overview of the purpose and contribution of each section is presented as follows:

### 2.1.1 Demystifying Electricity Markets

Electricity markets are complex systems built on principles of economics and power systems. However, these principles are often presented independently. Additionally, there are a variety of approaches to energy market structuring with no clear benchmark. As a result, electricity market organisation is often debated. Section 2.2 addresses these research gaps by reviewing various areas of electricity markets and presenting the key elements of economics and power systems in a unified approach. It also identifies common risks of electricity markets and proposes possible mitigation strategies.

### 2.1.2 Conventional Pricing Strategies for Power Systems

Demand response is a promising short-term energy management solution that incentivises users to adjust their load demand at various times to promote peak load reduction and load profile flattening. Dynamic pricing can be used to introduce robust demand response. However, traditional electricity pricing schemes disregard these advanced pricing schemes. Section 2.3 presents a comprehensive overview of key pricing strategies from a general and power system perspective that may be integrated to enable more fair and reliable electricity pricing.

### 2.1.3 Machine Learning Applications in Energy Forecasting in Electricity Markets

Energy management in electricity markets is a relatively complex task requiring the instantaneous balancing of supply and demand power. Inefficient energy management can disrupt normal power system operations and inconvenience electricity users. As a result, energy forecasting is employed by market operators for resource optimisation and contingency management. However, the forecasting process may be tedious when considering the dynamic and diverse natures of electricity generation and consumption. Machine learning is well-suited for this application as it can dynamically generate specialised forecast models using naturally abundant data from smart microgrids. Section 2.4 presents a systematic and in-depth review of machine learning and its current applications in electricity consumption and solar generation forecasting. Solar generation prediction is considered over other electricity sources as it is a popular DC-based renewable energy source with intermittent characteristics.

### 2.1.4 The Uprising of Blockchain Technology in the Energy Market Industry

Blockchain technology exhibits the potential to address some of the challenges of inequitable energy market facilitation by eliminating the need for intermediaries and centralisation. The technology offers additional advantages of enhanced security, immutability and transparency. However, several barriers hinder its official adoption, such as the apparent lack of deployable infrastructure for scalable applications, the unsustainable energy consumption of some consensus mechanisms, the unmet regulatory implications, insufficient incentive for large-scale entity collaboration, the distinct lack of governance, the risk of rogue distributed autonomous agents and the elevated risks of privacy infringement and illegal usage. These barriers can be addressed with increased awareness, public incentives, policy inducement and extensive research. Section 2.5 aims to promote awareness regarding blockchain technology and its role in transforming the energy market industry through a comprehensive literature review. It further assists in identifying opportunities for future research.

## 2.2 DEMYSTIFYING ELECTRICITY MARKETS

### 2.2.1 Background

Access to electricity is increasingly recognised worldwide as a basic human right and an essential factor in socio-economic development [18]. However, the power infrastructure in the vast amount of the energy sectors is traditionally monopolised by governments [19]. As a result, collaborative efforts focus on reforming the energy sector. One approach is introducing electricity deregulation, which may be incorporated through electricity trading in energy markets. The system offers the advantage of significantly reducing the cost of electricity while allowing utilities to generate revenue without compromising the reliability and security of the grid [20]. Energy markets further improve grid reliability and reduce electricity costs through demand response [21].

### 2.2.2 The Economics of Energy Markets

#### 2.2.2.1 Modelled Micro-economics

A market consists of different classes of participants, which are typically producers and consumers. The behaviours of these participants can be modelled through linear cost and utility functions, respectively [22]. The cost function has an upward gradient representing the electricity cost. In contrast, the utility function has a downward gradient representing consumer preferences. Natural operation occurs at various points of these functions, depending on the market characteristics. However, the most optimal operation occurs at the intersection point between these two functions, known as the market-clearing price [23].

#### 2.2.2.2 Continuous and Discrete Electricity Markets

Electricity trading interactions between participants are traditionally facilitated through continuous or discrete markets [24]. The former employs continuous bid matching among participants, with bid matching performed in real-time through auction mechanisms [25]. In contrast, discrete trading is performed periodically, relying on uniform pricing mechanisms. However, it is favoured for applications with limited integration capital [26].

#### 2.2.2.3 Single-sided Markets

Single-sided markets account for bids from only one class of participants. Uniform electricity prices are then enforced to ensure price equality among participants. The uniform market price is obtained by determining the lowest bid that enables equilibrium for the aggregate electricity supply and demand [27]. These markets are favoured for practical applications due to ease of implementation, promotion of price discovery and ensuring fair pricing among market participants [28].

#### 2.2.2.4 Double-sided Markets

Double-sided markets differ from standard single-sided markets as they consider bids and offers from both sides of market participants. The nature of this approach is well-suited for market power management and the social welfare of the electricity market [29]. Double-sided auctions are facilitated by matching bids in favour of electricity producers. As a result, if the consumer bids are unfavourable, no exchanges are initiated and the mechanism remains on standby for new bids [30].

#### 2.2.2.5 Electricity Exchanges

Electricity exchanges are platforms that facilitate electricity trading by serving as an intermediary between all market participants [31]. These platforms have recently transitioned to internet-based interfaces promoting greater accessibility. Additional benefits of these platforms are enhanced price competitiveness, transparency and liquidity of electricity markets [32].

### 2.2.3 Electric Power System Basics

Electricity markets primarily focus on traditional three-phase alternating current (AC) power operations. However, recent advancements in technology and research have led to considerations of direct current or hybrid (AC and DC) power operation [33]. One approach to DC operation is through the incorporation of DC microgrids as described by Fig. 2.1. Nevertheless, a generalised architecture is observable in power systems with three key elements. An overview of these elements is presented as follows:

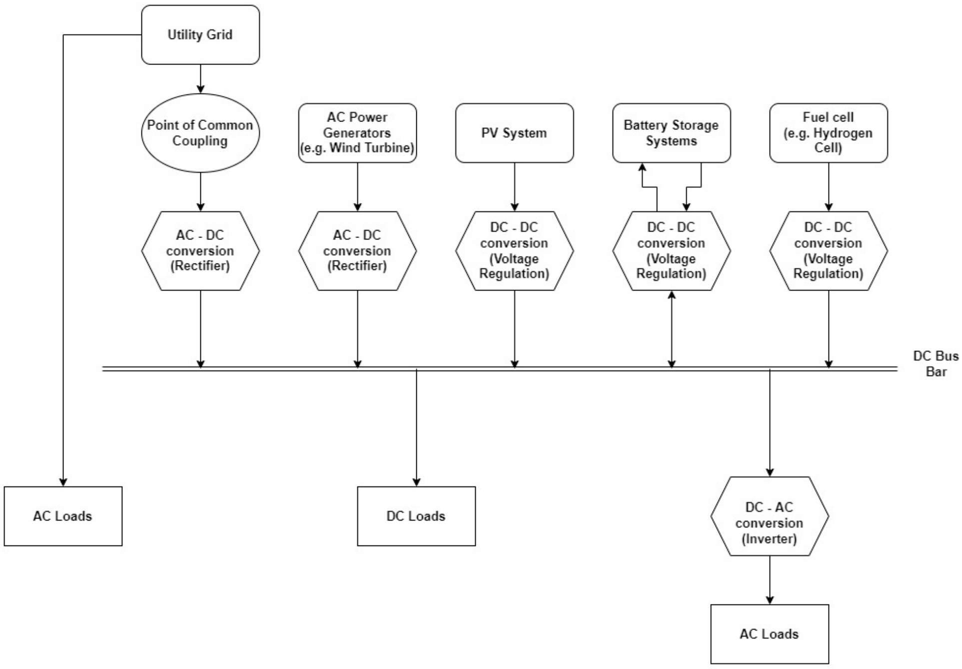



**Figure 2.1.** Block diagram demonstrating a conventional DC microgrid structure

#### 2.2.3.1 Generators

Electricity generation is performed at this stage which entails converting primary energy sources (e.g. fossil fuels, nuclear, wind and natural gas) into electrical power, commonly through turbines connected to generator shafts [34]. In turn, generators employ the electromagnetic induction principle to produce electricity. The primary energy sources can further be distinguished into non-renewable and renewable by evaluating the natural replenishment capabilities of the sources [35].

Conventional power networks accommodate large-scale electricity production plants through centralised configurations. Fossil fuel-based production plants are commonly used to cater for reliable and large-scale electricity production requirements, with coal-generation plants being the predominant form of electricity generation [36]. However, distributed smaller-scale electricity production is becoming more feasible due to rapid research and technological advancements. Distributed electricity generation decreases the complexities, power losses and costs associated with electricity transmission and distribution by placing electricity generators near the point of electricity demand [37]. Presently, solar and wind energy have emerged as the most viable options for this type of generation configuration when considering the natural abundance of these resources [38].

#### 2.2.3.2 Network

The network is responsible for interfacing electricity generators and consumers in power systems [39]. Typical infrastructure and equipment in this section include power electronics, poles, monitoring and communication systems, and cabling (overhead, ground or combination). The network caters for transmission and distribution stages within the electrical grid, with each aspect being distinguishable by the operating electricity voltage level.

The transmission stage is employed to transmit electricity over long distances through transmission lines. It typically occurs at increased voltages (e.g. 115 kV), from power converters (e.g. step-up transformers), for enhanced power efficiency. However, the transmission voltage levels depend on the practicalities of tower heights, insulator sizes, distances between conductors and the right-of-way width [40].

The distribution system consists of three subsystems: distribution substation, primary distribution and secondary distribution. The distribution substation is placed at the receiving end of the transmission stage and transfers its power to feeders. The feeders are typically in a radial, loop, or network configuration [41]. This subsystem is responsible for voltage transformation, switching, protection, voltage regulation and metering. The primary distribution system supplies power from the substation through the main feeders to the secondary distribution system. It operates at reduced medium-level voltages, such as 11 and 25 kV, with the aid of step-down transformers. This strategy allows for increased power-carrying capacity in cases where transmission stage requirements are no longer suitable. The secondary distribution stage emanates from the primary distribution stage through laterals branching from main feeders to residential and business regions before undergoing a final stage of voltage level reduction for end usage (e.g. 230 and 400 V) [42].

Furthermore, electrical power networks have promising prospects, with some slowly upgraded through smart grid technology integration. The technology equips power networks with the advanced features necessary to cater to rising electrical demand requirements. Some essential features in smart grids are enhanced reliability, security, demand side management, metering, interconnectivity, renewable resource integration and self-healing capabilities [43].

#### 2.2.3.3 Loads

Loads correspond to the electrical components of end users (e.g. appliances and lights) that expend the electricity supplied from the power network [44]. These components often transform electrical energy into more desirable forms of energy such as motion, sound, light and heat. Power is often employed to measure this rate of electrical transfer. There are three fundamental types of electrical loads, which can be classified by their power consumption properties under alternating current (AC) power configurations. These loads are capacitative, inductive and resistive. In direct current power configurations, electrical loads are modelled as purely resistive electrical components [45].

These electrical loads are often employed in conjunction with other loads, which collectively make up the electrical demand of end users. However, the demand depends on the physical and behavioural factors of power consumers [46]. For these reasons, electrical demands may be regarded as complex non-linear systems [47]. As a result, load characteristics are often modelled through generalised ratios such as load factor, loss factor, demand factor, utilisation factor and diversity factor [48, 49].

### 2.2.4 The Role of System Operators in Electricity Markets

Electricity markets require supply and demand management to avoid power system instability [50]. Power system operators are responsible for facilitating this process whilst ensuring optimal capital usage [51]. They achieve these requirements through the following roles:

#### 2.2.4.1 Ensuring Optimal Dispatch

Optimal dispatch is necessary to ensure that generational capacity is effectively coordinated to cater to the electricity demand at the least cost [52]. It further provides consistency in performance standards set by power systems. Optimal dynamic dispatch is gaining traction due to its ability to account for significant demand variations compared to standard static dispatches. It builds on conventional approaches by considering forecasted generation schedules whilst accounting for coupling constraints such as generator ramp rate [53].

#### 2.2.4.2 Managing Ancillary Services

System operators are responsible for contingency management to compensate for real-time energy mismatches from load fluctuations, power system component failure or generational units going offline [54]. In such cases, additional power generation capacity may be required. This flexibility is made possible through dynamic coordination of ancillary services [55].

#### 2.2.4.3 Performing Forecasts

There is a great deal of uncertainty introduced in electricity markets when considering the variability of electricity generation and demand profiles. Electricity forecasting is commonly employed to reduce this uncertainty. The operators carefully review the forecasts to gauge the electricity delivery requirements of the power system to effectively perform energy resource optimisation, network reconfiguration, voltage control and maintenance scheduling [56].

### 2.2.5 Electricity Market Risks and Possible Mitigation Approaches

#### 2.2.5.1 Abuse of Market Power

Market power refers to a market participant's ability to manipulate the market price by intentionally influencing supply and demand levels or both [57]. There are intrinsic risks of market power abuse in electricity markets, which negatively impact participants' economic welfare and introduce inefficient power management. Implementing stricter regulation measures such as price caps and bidding restrictions are suggested strategies for limiting market power [58].

#### 2.2.5.2 Inadequate Generation Capacity Investment

Market rules such as price caps are used for economic regulations among participants. However, these rules often deter adequate levels of generational capacity investment [59]. Inadequate generation infrastructure investment presents a challenge to market competitiveness in regions with sparse electricity generators. It further contributes to inefficient operation and hindrance of demand response incentives. Incorporating complementary capacity markets can be a feasible solution to this challenge by offering more reliable remuneration opportunities [60].

#### 2.2.5.3 Capacity Mechanism Price Distortion

Capacity mechanisms, such as auxiliary services, are employed in electricity markets for added electricity generation flexibility. It functions by compensating power generators for the availability of their power capacity. These mechanisms incentivise reserve margins and enhance power supply reliability and stability [61]. However, price distortion may occur in electricity markets due to the uniform nature of compensation in capacity markets regardless of market conditions [62]. Price distortion can be avoided by implementing dynamic pricing or introducing voluntary organised markets offering compensation through electricity discounts [63].

#### 2.2.5.4 Market Price Volatility

Significant and aggressive price variations can occur in the short term, known as price volatility, from low market liquidity. These occurrences deter trading among electricity market participants [64]. The extent of price volatility is influenced by the nature of energy sources in electricity markets. Markets incorporating intermittent energy sources like wind power exhibit more volatile price action than markets relying on stable energy sources like fossil fuels [65]. Adapting price-maker trading strategies and integrating virtual bidding are promising approaches to reducing price volatility [66].

## 2.3 CONVENTIONAL PRICING STRATEGIES FOR POWER SYSTEMS

### 2.3.1 Background

Fossil fuels cater for a significant portion of worldwide energy demand [67]. However, these energy sources are non-renewable, with them being depleted at rates that cannot be replenished. As a result, action is necessary to avoid a global energy crisis. A clear solution is the integration of renewable energy sources, which is fast-tracked in many countries worldwide [68]. Despite renewable energy sources presenting an opportunity for sustainable and clean electricity production, there are challenges of their own. The key challenges are related to generation intermittency, intensive investments, regulations and power system infrastructure modernisation [69]. Shorter-term action is much-needed in the interim. Demand response through the integration of electricity pricing strategies holds great potential as users are incentivised to shift their load profiles to minimise electricity costs [70].

### 2.3.2 General Commercial Pricing Strategies

There are numerous pricing approaches when considering general commercial environments. These pricing methods can be categorised as being cost-oriented or market-oriented. Further details of each category are discussed as follows:

#### 2.3.2.1 Cost-oriented Pricing

Cost-oriented pricing is typically dictated by the total cost of production (fixed and variable). However, it can be influenced by other factors leading to adaptable pricing models such as cost-plus, markup and target return. Cost-plus pricing is driven by simplicity. The scheme employs a fixed profit margin, known as the markup, applied to the total cost of production [71]. Markup pricing is a variation of cost-plus pricing except that the markup price is calculated on the desired selling price. This pricing strategy is typically employed when calculating the cost of production is impractical [72]. Target return pricing also employs the cost of production. However, it is driven by a predetermined target rate of return on investment instead of markup [73]. This approach enables companies to stay competitive by making cost adjustments. However, the reliability of the pricing scheme is influenced by the accuracy of the considered projections [74].

#### 2.3.2.2 Market-oriented Pricing

Market-oriented pricing considers market conditions and can be subsumed by the following pricing approaches: perceived-value pricing, value-based pricing and going-rate pricing.

Perceived-value pricing is a pricing strategy that dictates prices by customer perception of the item/service for sale. It entails accounting for the essential components of customer value: product quality, service quality and price. These components are then employed as a ratio of the customer's value earned to the price paid [75].

Value-based pricing is structured around optimising the value of the product/service to the price. The pricing strategy contributes to market competitiveness by providing value orientation through customer-value or economic-value modelling approaches [76].

Going-rate pricing accounts for product/service competition as a critical component in price determination. The extent to which competitor prices are accounted for depends on relative market strength and the company's nature. Differentiated companies typically adopt higher prices than the going rate, whereas price-oriented firms adopt lower prices [77].

Differential pricing, also known as price discrimination, determines prices according to customer characteristics. This flexible pricing approach encourages market competition and innovation [78].

Dynamic pricing offers the greatest flexibility, with the prices influenced by a combination of factors. Key considerations include customer behaviours, market prices, market structure, product demand, perceived value and seasonality. This pricing scheme offers consistent price adaption and accuracy. However, there is a strong reliance on advanced monitoring technology and electronic sale environments [79].

### 2.3.3 Electricity Pricing Strategies

Short-term and volatile peaks commonly occur in electricity load profiles due to mismanaged electricity demand. These peaks present challenges for power systems as additional generation capacity is required to cater for this significantly larger electricity demand [80]. Dispatching reserve capacity introduces a source of inefficiency in power systems as capacity generators are idle during off-peak hours.

Flat or block pricing is typically employed in retail electricity markets for simplicity. However, these pricing approaches do not promote adequate demand response or reflect the costs associated with electricity production and distribution [81]. Further research into demand management through electricity price strategies is necessary to counter peaks in electricity load profiles. Two conventional electricity pricing categories exist in the literature: time-of-use or area-based. Further details of each category are provided as follows:

#### 2.3.3.1 Time of Use

Time-of-use (TOU) pricing models are a demand response strategy that varies the electricity tariff according to the time of the day. It promotes load demand shifts to off-peak periods by offering consumers electricity bill reduction opportunities [82]. There are three forms of TOU strategies - static, dynamic and hybrid.

Static TOU price strategies determine electricity rates in advance, with prices remaining constant for longer intervals (e.g. several hours). Electricity prices depend on the time of day, day of week or season, with demand response incentivised by higher rates at peak periods. The nature of this TOU strategy provides greater certainty for consumers [83].

Dynamic TOU price strategies use fixed price points at various times of the day. The granularity of the pricing iterations depends on the demand response required. However, additional automation technology may be necessary to manage the end user's demand for smaller time frames to promote greater price sensitivity [84].

Lastly, there are hybrid price strategies, such as critical peak pricing (CPP). CPP offers greater implementation feasibility by combining properties of static and dynamic TOU price strategies to produce a more flexible tariff mechanism. There are four schemes for CPP: fixed-period, variable-period, variable peak pricing and critical peak rebates [85]. The technique functions by forecasting critical events and applying decision mechanisms to set prices, such as in times of high demand. Thus, contributing to peak load reduction. However, this approach may result in significant price deviations as much as five times larger than baseline tariffs [86].

#### 2.3.3.2 Area-based Pricing

Power grids may be subjected to constraints that need to be managed. An example of a constraint is network congestion which occurs when transmission utilities cannot transmit the power required to supply load demand [87]. In these cases, time-of-use tariffs may not be optimal as not all areas of the power system are affected. Area-based pricing addresses this challenge by strategically adjusting electricity prices at a granular spatial level within a grid. This pricing approach further contributes to short-term economic benefits for generators, such as reduced costs of production [88]. There are two fundamental approaches to area-based pricing: zone pricing and locational marginal pricing.

Zone pricing, also known as regional pricing, is typically integrated into more extensive energy markets. Zones are formulated according to available electricity transfer capacity by considering energy balance conditions and transmission line capacities. Zone detection algorithms, such as k-means clustering and spatially constrained clustering, can also be used to improve this process [89]. This price strategy has increased market liquidity due to its consideration of node clusters. As a result, there is greater price stability and market competitiveness compared to more granular pricing strategies. However, the price signals converge toward nodal price averages and neglect internal constraints leading to price inefficiencies and inaccuracies [90].

Locational marginal pricing (LMP), or nodal pricing, is the second approach. It dynamically manages electricity prices at strategically fixed points (nodes) across the grid by accounting for the costs of marginal generation, loss and transmission congestion [91]. LMP results in more accurate prices compared to zonal pricing by considering constraints on net nodal injections [92]. Despite the advantages of this pricing strategy, there is adoption resistance by stakeholders. The biggest arguments against its application are attributed to market design complexity and the lack of market operation transparency [93].

## 2.4 MACHINE LEARNING APPLICATIONS IN ENERGY FORECASTING IN ELECTRICITY MARKETS

### 2.4.1 Background

The application of machine learning in decision-making is currently a trending research area attributed to accelerated technological advancement and the increased availability of data. Machine learning enables the convenient conversion of data sets into models at reduced computational efforts of users. These models are then optimised through intelligent learning techniques [94]. Its applications can be generalised under three primary research areas: task-oriented studies, cognitive simulation and theoretical analysis [95]. Machine learning applications in power systems are mostly task-oriented, with usages in energy management. It enables more accurate power system planning and scheduling through energy generation and consumption forecasting [96, 97].

### 2.4.2 Machine Learning Foundations

#### 2.4.2.1 Machine Learning Types

The field of machine learning is diverse and can be classified according to the learning strategy applied. An overview of available machine learning classes is presented in Fig. 2.2.

Supervised learning is a popular machine learning choice. It requires input and labelled output data for training. It then employs relationship identification to generate a function that maps the input data to the labelled output data. Furthermore, there are two main supervised models: regression and classification models. In cases where the data is continuous, regression techniques are employed. On the other hand, categorization models are employed if the data is discrete [98].

Unsupervised learning is similar to supervised learning as it requires input data. However, it differs as it does not require labelled data. As a result, unsupervised learning is a feasible option for conditions when outputs in the study are not clearly defined. The learning method removes the need for labelled data by identifying patterns and characteristics within the input data. However, the clustering techniques employed in this process cannot guarantee a globally optimum solution [99].

Semi-supervised learning offers a hybrid solution between supervised and unsupervised learning by training models from a combination of unlabelled and labelled data. This option is feasible when considering the practical limitations of labelling data, such as the cost, computational and skill requirements [100].

Reinforcement learning employs a *trial-and-error* learning approach. As a result, no defined outcomes are required. Optimisation of the model is iteratively performed. The learning approach interacts with the environment and employs feedback mechanisms to determine suitable modelling directions [101].

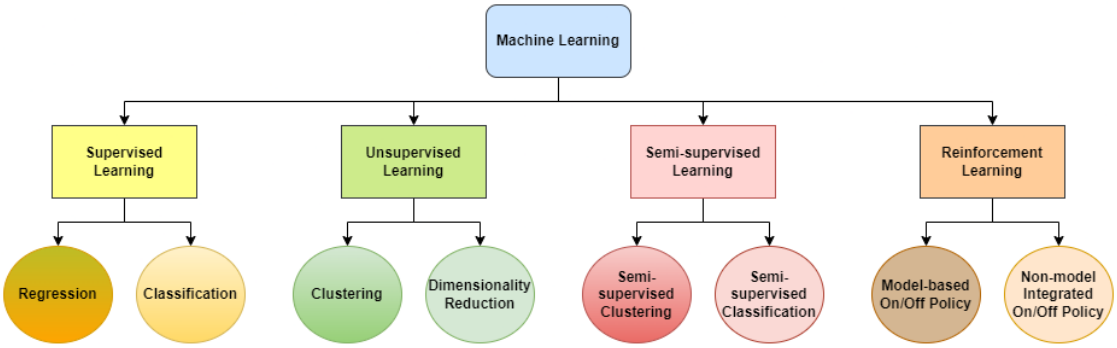



**Figure 2.2.** An overview of available machine learning classes

#### 2.4.2.2 A Generic Approach to Machine Learning

The selection criteria for machine learning approaches depend on the nature of the available data and the required application. In general, supervised and unsupervised learning are employed for scenarios based on data analysis and reinforcement learning is favoured for applications requiring decision-making or comparisons [102]. A generic approach to solving machine learning problems is possible despite the selection of various machine learning types, as summarised in Fig. 2.3.

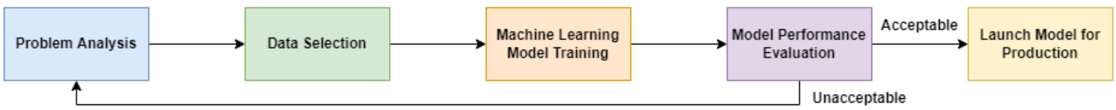



**Figure 2.3.** A generic approach to solving machine learning problems

#### 2.4.2.3 Standard Performance Metrics

There are numerous metrics available to evaluate the effectiveness of machine learning models, such as mean absolute percent error (MAPE), R square ($R^2$), mean absolute error (MAE) and mean squared error (MSE) [103]. These performance metrics are discussed as follows.

The MAPE is an indicator of the model's prediction accuracy in terms of the unsigned percentage error and is determined by [104]:

$$\text{MAPE} = \frac{100}{n}\sum\left|\frac{ym_t - yo_t}{ym_t}\right|, \tag{2.1}$$

where $n$ is the number of data values, $y$ is the predicted value and $yo_t$ is the actual/observed value.

The R square corresponds to the regression score (R-score), which closely represents the accuracy of predictions and is determined through [104]:

$$R^2 = \frac{(\sum_{t=1}^{n}(yo_t - \bar{y}_o)(ym_t - y\bar{m}))^2}{\sum_{t=1}^{n}(yo_t - \bar{y}_o)^2 \sum_{t=1}^{n}(ym_t - y\bar{m})^2}, \tag{2.2}$$

where $y\bar{m}$ is the mean predicted value and $y\bar{o}$ is the mean actual/observed value.

MAE is employed to evaluate the closeness of forecasts to actual target outcomes and is obtained with the following equation [104]:

$$\text{MAE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}||(yo_t - ym_t)||}. \tag{2.3}$$

MSE measures the average of the squared errors between targets and predictions. This indicator places significance on statistical outliers and is determined by [104]:

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}(yo_t - ym_t)^2. \tag{2.4}$$

#### 2.4.2.4 Important Considerations in Machine Learning Model Selection

Two fundamental properties should be considered when selecting a model for implementation: bias and variance [105]. A high model variance accounts for intricate modelling by fitting closely to the data. However, the models perform inadequately for generalisations. In contrast, models with high bias fit the data loosely, resulting in simple and inflexible modelling. However, these models perform poorly for complex hypotheses [106]. As a result, a trade-off exists between bias and variance in model selections.

### 2.4.3 Machine Learning Applications in Electricity Demand Forecasting

#### 2.4.3.1 Electricity Demand

Electricity forms the backbone of modern civilisation, with many homes and businesses relying heavily on it. Due to climate changes and technological advancements (e.g. electric vehicles), electricity demand is rapidly increasing. This demand needs to be carefully managed to avoid an energy crisis [107, 108]. However, it is challenging to manage electricity demand due to its continuously varying and complex nature. The electricity demand of an entity can be modelled as a function dependent on numerous external factors such as weather conditions, geographical diversity, season, sunrise/sunset time, social standards and demography [109].

#### 2.4.3.2 The Importance of Electricity Demand Forecasts

Electricity demand forecasting can significantly improve demand-side management by serving as a platform for the precise coupling between electricity generation and demand. It reduces the level of uncertainty for grid operators and planners to effectively plan and make informed decisions [110]. Electricity demand forecasting is performed across a variety of time frames. Long-term forecasting is employed for capacity planning and typically accounts for economic and demographic variables. Medium-term forecasting aid in the scheduling, maintenance and economic dispatch of resources. Lastly, short-term forecasting is employed in daily electricity market coordination and bidding optimisation [111].

#### 2.4.3.3 The Role of Machine Learning in Electricity Demand Forecasts

Electricity demand is highly dynamic, resulting in a complex multi-variable and multi-dimensional model. Conventional modelling methods rely heavily on approximations through classical and computational intelligence methods. Classical methods are inefficient for non-linear data, whereas computational intelligence methods are limited to handcrafted features and learning abilities. Machine learning can partially address these challenges and produce satisfactory results [112]. Various machine learning algorithms can cater for this application. However, some algorithms are more suitable, as demonstrated by the summary of the best-performing algorithms identified in Table 2.1.

**Table 2.1.** Summary of the performances of various machine learning algorithms for electricity demand forecasting identified in the literature

| Study Reference | Prediction Horison | Evaluation Criteria | Result Summary |
|---|---|---|---|
| [103] | Hourly | RMSE, MAPE, MAE | LSTM > SVM |
| [104] | Daily, Monthly, Annualy | $R^2$, MAPE | LR > RF > DT |
| [112] | Hourly | $R^2$, MAPE | RFR > DTR > KNN > GBR<br>GBR > MPR > ENR > SVR |
| [113] | Daily | Accuracy | NARX GP > LR (Quad)<br>LR (Quad) > LR (incl. int.)<br>LR (incl. int.) > LR > NN |
| [114] | Monthly | RMSE | LMR > ARIMA > MR > TS |
| [115] | Daily | MAE, MAPE, RMSE, $R^2$, Time | ExtraTrees > MLP > GP<br>GP > RF > KN<br>KN > Ridge > LR |
| [116] | Hourly | RMSE, nRMSE, MAPE | SVM > kNN > ANN |

### 2.4.4 Machine Learning Applications in Solar Generation Forecasting

#### 2.4.4.1 Solar Energy

Fossil fuels are the main contributors to the energy sector, despite being unsustainable and harmful to the environment. Consequently, global efforts are being focused on reviewing energy strategies and policies. Two key methods proposed are enhancing the extent of renewable energy penetration in power production and improving the efficiency of energy usage [117]. Solar photovoltaic (PV) panels enable rapid adoption rates of renewable electricity generation, with it presently contributing to 55% of the overall new renewable energy capacity [118]. PV panels contain solar cells which produce electricity from sunlight. However, the performance of these solar cells in electricity generation is influenced by external factors such as solar irradiance, temperature, panel shading, dust and soiling of the PV panels [119].

#### 2.4.4.2 The Need for Solar Generation Forecasting

Larger-scale integration of solar generation in power systems introduces uncertainty in grid management due to its natural intermittency. Improper management of these renewable energy sources can negatively impact the grid's power quality, stability and protection equipment [120]. Solar energy prediction can assist power system operators in making informed decisions in managing energy balances by forecasting solar production outputs [121]. Thus reducing uncertainties in the coordination process necessary for effective generation scheduling, unit commitment, economic dispatch, contingency planning, energy storage sizing, energy market policies, reliability assessments and reserve capacity management [122].

#### 2.4.4.3 The Role of Machine Learning Solar Energy Generation Forecasts

The input variables used to generate predictive models and forecasting horizons significantly influence the accuracy of forecasts. There are two categories of PV predictive models: direct and indirect. Direct models forecast PV outputs using historical data directly from the PV system. In contrast, indirect models aim to forecast meteorological variables such as solar irradiation that influence PV outputs. Indirect models are advantageous in scenarios with limited historical PV output data [123]. Furthermore, forecasting methods are subsumed by four classes: statistical, physical, artificial intelligence (AI) and hybrid. Machine learning is a subset of AI that displays excellent suitability for PV forecasting applications due to a relatively faster learning rate and regression capabilities [124]. A summary of the best-performing machine learning algorithms identified in the literature is provided in Table 2.2.

**Table 2.2.** Summary of the performances of various machine learning algorithms for solar generation forecasting identified in the literature

| Study Reference | Prediction Horison | Evaluation Criteria | Result Summary |
|---|---|---|---|
| [125] | Daily, Monthly | $R^2$, MAE | GBRT > GPR<br>GPR > XGBoost > RF |
| [126] | 5-minute | RMSE, MAE | ANN > KNN > SVM > LR |
| [127] | Daily | RMSE | SVM > ANN > ELM |
| [128] | Daily | MAPE | DL > SVR |
| [129] | Hourly | nRMSE | SVR > ANN > RF |
| [130] | Daily | MAE, RMSE | SVM-RBF-Kernel > SVML > LR |
| [131] | Hourly | $R^2$ | SVR > MLFFNN > ANFIS |
| [132] | Hourly | nRMSE | MLP > ARMA > SVR<br>SVR > Pruned RT > Boosted RT<br>Boosted RT > Bagged RT > SP<br>SP > RT > Persistance |

## 2.5 THE UPRISING OF BLOCKCHAIN TECHNOLOGY IN THE ENERGY MARKET INDUSTRY

### 2.5.1 Background

Coal-based power plants have been the predominant form of energy production worldwide due to benefits such as large-scale generational capacity, stable power production and their relatively lower construction costs and periods [133]. The global call for progressively reducing carbon emissions has offset research efforts from fossil fuel energy production to more environmentally friendly options, with photovoltaic and wind systems being popular choices [134]. The European Commission has further enforced this drive through the precise formulation of binding environmental targets set for the near future (2030) [135]. The possible extent of decarbonisation of the power sector can be undoubtedly enhanced by promoting localised renewable energy generation. Power network providers often employ traditional financial incentives for prosumers, such as feed-in tariffs. This holistic approach does not adequately account for decentralised energy ecosystems [136]. Another practical approach to promote localised energy production is rewarding prosumers through subsidies, which places unnecessary financial strain on governments and policymakers [137]. Shifting toward transactive energy through energy exchange mechanisms can overcome these shortcomings. Blockchains are a promising technology that can be used to cater for this application whilst promoting decentralised, transparent and secure market environments.

### 2.5.2 The Emerging Blockchain

#### 2.5.2.1 Defining a Blockchain

A blockchain is a complex data structure described as a distributed and immutable digital ledger. Each ledger record typically represents a specific block on the blockchain, whereas the cryptographical links serve as the continuous chain [138]. Furthermore, direct copies of the blockchain are equitably distributed across numerous independent nodes (active users of the network) to increase the reliability and transparency of the system. These essential characteristics improve the fundamental integrity and security of the system.

A generic blockchain is illustrated in Fig. 2.4. It typically contains four elements: valuable data, timestamp, hash and previous hash. The data can be in any digital form; however, data capacity limitations exist. Timestamps indicate when a specific block was appended to the chain. Unix timestamps are frequently employed due to their versatility across various digital systems. The hash may be traditionally regarded as an encrypted identifier for data obtained from a hashing algorithm. Lastly, the previous block's hash is contained in a block for enhanced security. This distinctive feature presents a challenge to subtly altering a block without having an apparent mismatch to the hash record stored in the subsequent block [139].

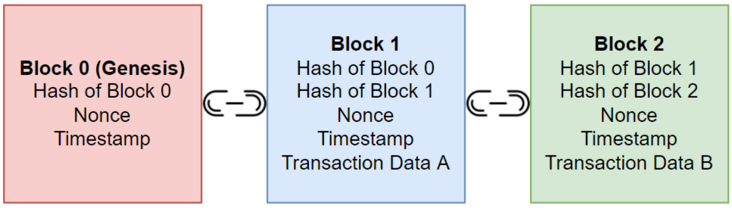



**Figure 2.4.** An example of a blockchain consisting of numerous blocks

#### 2.5.2.2 Types of Blockchains

Four types of blockchain exist [140]. The first type is the public blockchain which is accessible by the public. These chains are popular as they enable anyone to actively participate in the network without permission from an authority. Transparency increases trust and may be regarded as a strategic asset; however, it may also be perceived as a strategic risk. For instance, marketing and trading strategies may be imitated by competitors. This form of transparency may jeopardise an organisation. As a result, private blockchains may be employed. These blockchains enforce restrictions on access to the network [141]. It also does not require a trusted protocol to make transparency a design choice and is commonly governed by centralised authorities such as the government [142]. Hybrid blockchains are less popular blockchains that combine characteristics of public and private blockchains. The last blockchain type is sidechains. This form of technology is an accessory to the blockchain as they run parallel to the main chain. They enhance the efficiency and scalability of the system [143].

#### 2.5.2.3 The Key Principles of Blockchains

The original Bitcoin white paper highlighted the potential application of a particular protocol; however, several key principles for general blockchain technology can be implicitly identified [144]. These principles enable general blockchains to regulate, validate and secure transactions efficiently. Various aspects of some of the principles are discussed further.

The first principle is network integrity. Four values are necessary for ensuring a network's integrity is not breached – honesty, accountability, deliberation, and transparency. Transparency is a prevalent trait of blockchain implementation since it provides an effective means to counter corruption and fraud [144]. Conventional systems contain centralised registries with a lack of trust among immediate parties, resulting in the dependence on third parties' involvement as intermediaries. A distributed ledger can counter this as it is naturally transparent and reliable. It typically achieves this by equitably distributing extensive knowledge in the system and enhancing attribution, such as asset origins and ownership history [145]. The other three values can be ensured by applying reliable consensus mechanisms among independent nodes in the network. This powerful feature ensures consistency and validity of the blockchain [146].

The second principle is the distribution of power. There is an intrinsic risk of malicious attacks in digital networks, particularly centralised ones. Consequently, a blockchain network should be able to defend against network attacks relentlessly. Blockchains can achieve this by operating in a decentralised manner with a distribution of network control. This feature rapidly improves the strength of defence and reliability of a network since there is no single point of attack [145]. Mass collaboration among independent network facilitators is therefore required to maintain the blockchain. The resiliency and reliability of the network are increased when there is an expansion in the distribution of power. Furthermore, modern mining algorithms incorporate more innovative techniques requiring application-specific integrated circuits, cloud mining and mining pools [147].

The third principle is privacy. Every individual is entitled to their privacy; however, the digital age has taken away the control of each user's privacy with the user's private information gathered and made readily available. Blockchain enables users to have control of their unique identity by conventionally representing individuals pseudonymously in the form of public addresses. In doing so, no personal information is required from the network's users [148].

The fourth principle is incentivised commitment. Due to the decentralisation of a blockchain, independent network facilitators (miners) should be committed to steadfastly maintaining the integrity and security of the network. For this key concept to function efficiently, there must be value established as a direct incentive [149]. This value is typically enforced through a digital token such as bitcoin. Independent miners are then incentivised to faithfully serve the network by ensuring the secure and effective functioning of the system. Collaboration is naturally encouraged as a direct result. Monetary policies are developed in software to control these rewards issuing. Effective strategies such as reward halving can also be incorporated to promote deflation and increase the token's monetary value, further contributing to an enhanced incentive to users [150].

The fifth principle is security. There are numerous security threats to digital systems in the modern-day, such as hacking and phishing [146]. It is, therefore, imperative that systems can prevent these potential threats by incorporating security as a design principle. This fundamental principle is responsible for providing confidentiality, non-repudiation and authenticity of the network. Cryptography is typically utilised to ensure the security of the blockchain is withheld [151].

The sixth principle is inclusion. A blockchain network should promote the participation of any individual with no discrimination. This essential characteristic can be achieved by eliminating the specific need for personal information such as the unique identity of a user [144].

#### 2.5.2.4 Secured through Cryptography

The concept of a hash stems from the idea that a fingerprint is a person's unique identifier. Hashing algorithms have been developed to securely map digital data to a finite data set in the form of a hash. Numerous hashing algorithms exist; however, some are more secure and reliable than others [152]. These algorithms have five requirements: one-way operation, deterministic, fast computational rates, avalanche effect and collision resistance. The hash can be utilised to determine if data has been altered efficiently, thus serving a significant role in the reliability and accountability of blockchain technology [153].

The SHA256 is a popular hashing algorithm employed in blockchains. It analyses digital data to produce a hash of 256 bits, equivalent to 64 characters. The main steps in the algorithm are portrayed in [154].

#### 2.5.2.5 Consensus Protocols

Validation of a new block and overall blockchain is required before expanding a chain. The consensus among miners (specialised blockchain network participants) is also necessary for two purposes. Firstly, it protects the network from attackers. It achieves this by ensuring that the distributed ledgers are continuously synchronised and invalid chains are removed from the system. Attackers would have to instantaneously alter the majority of the distributed blockchains before synchronisation occurs. Consequently, this feature enables blockchain to be regarded as immutable. Secondly, a consensus protocol caters for conflicting chains in the network by ensuring the network conforms to the longest instantaneous blockchain [155].

A blockchain trilemma exists when collectively considering the three fundamental properties of blockchain technologies (decentralisation, scalability and security) [156]. Present consensus methods are not able to achieve optimisation in all areas. For instance, decentralisation requires decisions to be performed through consensus among distributed nodes in the blockchain. As a result, transactional speeds are reduced. On the other hand, the scalability of the system is necessary for mass adoption, which will require faster transactional rates due to the increased number of transactions. Security is an area that often gets neglected. Proof-of-Work (PoW) and Proof-of-Stake (PoS) are the most common mechanisms for consensus [157]. PoW offers the most significant security at the expense of extensive energy usage and transaction processing rates. At the same time, PoS demonstrates enhanced transactional processing costs and rates with an intrinsic limitation on security. On occasion, a hybrid protocol is adapted [158].

The PoW protocol requires mining to be performed. Mining is the process in which numerous nodes compete to add a block to the blockchain, with the winner receiving a financial incentive. Miners iteratively generate nonce values until the block's hash is within a predetermined target hash range. The nonce is a 4-byte field, which increases from 0 until a desirable hash calculation is achieved [159].

### 2.5.3 The Revolutionary Smart Contract

#### 2.5.3.1 Improving the Traditional Contract

Contracts are an essential aspect of legal-binding agreements. They are responsible for governing rights and duties among multiple parties. It achieves this by clearly defining the terms of agreements whilst depicting rewards and possible penalties. Traditional contracts are written or oral form. Challenges arise in executing the agreements without enforcement, occasionally requiring litigation [160]. As a result, there is unnecessary consumption of valuable resources. The novel concept of smart contracts has been introduced to address this challenge by ensuring compliance with a contract [161]. It can achieve automatic and impartial execution due to its inability to be revoked or stopped. These revolutionary contracts are intended as complementary tools to improve the judicial system progressively and should be used in synergy with traditional contracts [162].

#### 2.5.3.2 The Inner Workings of Smart Contracts

Smart contracts are executable computer programmes that are typically deployed on blockchain ledgers [163]. They reliably enforce the terms of contracts by making use of independent and distributed nodes. By eliminating intermediaries, ancillary costs (from administration and services) and potential risks of tampering can be significantly reduced [164]. Various benefits naturally arise from utilising these contracts, primarily improved computational input, predictability and security. Smart contracts are utilised for three essential purposes. Firstly, they rigorously enforce contractual terms. Secondly, they eliminate the need for an intermediary by enabling a reliable and unbiased interaction. In doing so, a cost-benefit arises. Lastly, they ensure that the moral integrity of both parties is upheld [165].

A smart contract is guaranteed to act in the same manner and is auto-executable. It achieves this by transferring the contract terms into software capable of automatically executing once all conditions have been adequately met [160]. Necessary conditions are continuously monitored with advanced algorithms and sophisticated sensors. The usage of programming logic promotes impartiality in its execution, whereas traditional contracts rely on human judgement. Impartiality is achieved by incorporating programming languages characterised by uniform computational logic and successful execution regardless of external factors. Furthermore, the consensus algorithms employed on distributed blockchains mitigate the potential risks from deliberate manipulation or false contract execution. The shared database enables key nodes to validate the conditions and actions of the contract [166].

#### 2.5.3.3 Operational Phases in Smart Contracts

There are four operational phases when considering generic smart contracts from a practical perspective. These distinct phases can be classified as search, negotiation, performance and post-performance incentives. During the search phase, parties discover and survey each other. This phase is followed by negotiation, which entails creating the agreed-upon terms and conditions of the contract. The committed parties then proceed to the performance phase. During this phase, performance is ensured by managing collaterals such as money, service, guarantee or product. In the previous phase, post-performance incentivising is performed by rating the opposing party. This phase is necessary for promoting the desirable outcome and can be achieved with a specific control structure — the structure assists in predicting the contract's outcome.

#### 2.5.3.4 Smart Contract's Lifecycle

Four stages can describe a smart contract's lifecycle: creation, deployment, execution, and completion [167]. In the creation stage, negotiation is performed among parties to determine the contract's terms. These terms are then transferred into the software before validating by the parties. The finalised smart contract is stored on a blockchain in the subsequent stage, and digital assets related to the contract are frozen. The execution stage occurs after that, which entails evaluating the contract conditions and automatically executing the contract when compliance has been fulfilled. Lastly, the state of the contract is updated with the digital assets released to the appropriate parties.

### 2.5.4 The Future of Energy Markets

#### 2.5.4.1 The Need for Localised Energy Trading

Increasing demand for sustainable energy usage has led to more significant adoption rates for renewable energy sources in distribution networks. Energy management systems are therefore necessary to counter the intermittence of renewable energy [168]. Peer-to-peer (P2P) energy management is a promising approach as it offers more considerable flexibility and convenience than traditional approaches such as centralised and multi-agent management [169]. P2P energy trading encourages more significant interaction between energy suppliers, consumers and prosumers. Power system users are incentivised to explore alternative forms of energy production. As a result, the penetration of renewable energy in a power network can be increased, improving the stability and efficiency of a network. Sophisticated bidding strategies can further be employed to optimise profitability and service delivery in these markets as proposed in [170].

#### 2.5.4.2 Technical Barriers Hindering P2P Trading

Numerous technical barriers hinder P2P trading systems. One of the most prominent barriers is the rigidness of traditional distribution networks. These networks cannot accommodate bidirectional energy flow [171]. Furthermore, centralised network configurations result in users accessing the power network at different sections [169]. Active distribution networks can overcome these barriers. These controllable energy systems accommodate distributed power generation, energy storage, and bidirectional energy flow [172]. Incorporating energy hubs can further enhance the involvement of energy ecosystem participants by interconnecting energy producers, prosumers, and consumers. Energy hubs accommodate the multi-generation nature of energy markets [173]. Multiple energy carriers in energy markets can be optimally coordinated within these hubs through stochastic and probabilistic approaches as described in [174] and [175], respectively. These game-theoretic approaches enhance the viability of integrated energy markets in energy hubs whilst presenting an opportunity for risk aversion.

#### 2.5.4.3 Blockchain Technology in Energy Markets

Blockchain technology can address the concerns of energy monopolisation and lack of transparency in energy exchanges. The technology can enable peer-to-peer energy exchanges in a decentralised manner [176]. It can facilitate energy exchanges in a secure, unbiased and reliable manner [177]. The concept of peer-to-peer (P2P) energy trading through blockchain technology has been implemented in a Brooklyn microgrid in New York. A framework for developing an efficient energy market in a microgrid has been proposed in [178]. Upon evaluation of the Brooklyn microgrid, it was partially compliant with the framework.

A wide variety of blockchain solutions are being developed at the moment. A blockchain selection procedure has been proposed in [141] to assist organisations in determining which technology is best suited to their needs. A layered approach to protocol integration is recommended in complex systems requiring scalability, decentralisation, and practicality. Layer 1 protocols represent the base architecture of networks, whereas layer 2 operates on layer 1 to improve the functionality and interoperability of the system [179]. This layered approach has been incorporated into a novel sharing system [180]. The blockchain ecosystem consists of a blockchain (layer 1), lightning network (layer 2) and smart contracts (layer 2). Specialised solutions are also being developed. For instance, a novel decentralised digital currency (NRGcoins) has been proposed in [181]. The currency has been developed to improve the feasibility and reliability of open currency exchange markets by employing a hybrid machine-learning algorithm.

There is a concentrated focus on deploying smart contracts for peer-to-peer energy markets facilitated on blockchains [182]. Smart contracts, commonly deployed by centralised power management systems, are incorporated to automate the transfer of funds in the network [183]. A blockchain system was proposed in a study of a game theory model, including energy storage demand-side management [184]. A consortium blockchain based on Zig-Ledger was developed as a rudimentary technological framework for energy exchanges. Smart contracts containing energy bids were then manually deployed on the blockchain. The system can be improved through the implementation of a decentralised application. A modest energy offer-based blockchain solution, without smart contracts, can also be employed for smaller-scale systems such as the one discussed in [185].

Furthermore, energy markets are being established, with public blockchains predominant. This approach challenges the supervision capabilities of power organisations as users can freely interact with the system. In addition, personal data is exposed. On the other hand, energy management performed on consortium blockchains addresses concerns of exposure privacy at the risk of malicious nodes registering false accounts and entering the system. A private blockchain system can address these concerns whilst enabling reduced communication delays; however, there is centralisation. An example of this approach has been deployed on a Hyperledger Fabric [169]. Another application of a private blockchain, built through MultiChain, is explored in [160], with a machine-to-machine transaction management method proposed.

## 2.6 CONCLUDING REMARKS

### 2.6.1 Demystifying Energy Markets

Electricity markets are promising approaches to power system deregulation whilst encouraging proactive energy ecosystems and demand response. These systems are built on principles of economics and power systems that ensure competitive access to the energy ecosystem. Common approaches to electricity markets have been reviewed, highlighting key characteristics. The shortcomings and challenges of present markets can be reduced by introducing a dynamic pricing strategy capable of addressing risks of price distortion, inadequate market investment, market power and volatility. Furthermore, there is a poor reflection of simulated energy market approaches in the present literature, contributing to less research and innovation in electricity markets.

### 2.6.2 Conventional Pricing Strategies for Power Systems

Conventional pricing strategies for electricity markets are built on principles of generic pricing strategies used in the commercial industry. Furthermore, the available literature predominantly focuses on electricity pricing strategies for traditional unidirectional power systems. However, technological advancements have enabled grids to be adapted to facilitate bidirectional power flow and advanced features such as automation and real-time data monitoring. Consequently, more sophisticated pricing strategies can now be realised.

Furthermore, the reviewed pricing schemes are naturally simplified and fail to adequately account for factors such as demand response and energy conditions. Dynamic pricing is well-suited for this application, enabling more fair, accurate and reliable prices. However, it is not being integrated into power systems worldwide. Various arguments hindering its adoption need to be addressed and are summarised as follows:

- The pricing concepts are relatively new
- Implementation of the strategies is capital-intensive and complex
- There is a lack of transparency in the pricing scheme contributing to price uncertainty
- The pricing strategies may be subjected to market power abuse

### 2.6.3 Machine Learning Applications in Energy Forecasting in Electricity Markets

Machine learning can significantly improve resource management and contingency planning in power systems by providing adaptable and robust forecast models without in-depth system analysis. Various algorithms can be used for this application. However, the *bias-variance* trade-off must be considered.

Despite the abundance of machine learning algorithms available, a small number have been investigated and presented in the literature. Furthermore, the present studies performed differ regarding data sets, forecasting horizons, performance measures and feature selections. As a result, there are competing findings. There is a lack of a uniform ground to make reliable deductions on the best-performing algorithms for energy forecasting applications such as solar generation and electricity demand prediction. Further research is required to address these research gaps.

### 2.6.4 The Uprising of Blockchain Technology in the Energy Market Industry

Blockchain technology possesses the potential to revolutionise the digital age. The applications for blockchains can be drastically improved when used in synergy with smart contracts. In doing so, energy exchange transactions can be enforced in a transparent, reliable and immutable environment. Modest blockchain technology applications are being investigated from a predominantly transactive perspective. Blockchain technology can potentially enable fully autonomous and decentralised energy ecosystems with more significant integration efforts in data storage, energy scheduling, intellectual property control, licensing automation, maintenance management, power flow monitoring, power quality regulation, resource management and tariff customisation.

# CHAPTER 3 METHODS FOR EQUITABLE ELECTRICITY MARKETS

## 3.1 CHAPTER OVERVIEW

Various conceptual frameworks, software and experiments have been formulated to address the identified research gaps. This chapter portrays the research methodology undertaken in the study. It consists of systematic research designs, study size selections, data collection, analysis methods, investigation approaches and appropriate case study considerations. An overview of the purpose and contribution of each section is presented as follows:

### 3.1.1 Investigating Traditional Electricity Market Approaches

Electricity markets are emerging concepts with limited practical implementations. There is a reliance on traditional approaches and a reluctance to consider more innovative approaches. A possible reason for this is a lack of research material and baseline references - especially for simulations of these markets. Section 3.2 strives to bridge this research gap by investigating case studies for various electricity market configurations, such as single-side and double-side. Pricing strategies for these markets are then considered to gain insight into each approach's inner workings and improvement opportunities. The implementation and solving process for each market pricing strategy is additionally provided.

### 3.1.2 Comparison of Popular Machine Learning Techniques for Short-Term Energy Forecasting

Short-term energy forecasting is often considered in electricity markets for efficient energy and price management. Machine learning can streamline this process by generating high-accuracy prediction models from data. There are a vast amount of training algorithms that can be used for this purpose. However, the selection of superior algorithms is challenging due to the inconsistency of forecasting horizons, datasets, feature selections, tuning parameters and performance metrics in the available literature. Section 3.3 aims to address this research gap by performing a baseline comparative analysis study on 42 different machine learning algorithms for 1-hour ahead electricity demand and solar radiance forecasting. In doing so, the best-performing machine learning algorithms for these applications can be identified. The complete training procedures for both applications are also included in this section.

### 3.1.3 Participant Matching Optimisation in Electricity Markets

Traditional electricity markets match participants through price-driven or energy-balance strategies. However, these approaches are inefficient when considering transmission power loss and congestion. Section 3.4 proposes an innovative participant matching strategy driven by transmission loss and congestion optimisation. The optimisation problem is formulated from constrained single-objective and multi-objective perspectives to determine the most efficient approach. Each approach is investigated through a case study and presented with the solving processes.

### 3.1.4 A Novel Approach to Dynamic Pricing in Electricity Markets

Pricing presents the opportunity to enhance energy management in power systems by unlocking greater degrees of demand response. However, non-optimal pricing strategies are predominantly adopted in the energy sector. Existing price schemes are not robust and do not adequately account for energy conditions and demand response. At the same time, inefficient market clearing pricing techniques are used in present electricity markets that may be subjected to market power abuse, manipulation and volatility. Present pricing techniques also inadequately stimulate generation capacity investment. Section 3.4 develops a novel dynamic pricing strategy to systematically cater to these identified shortcomings of current electricity pricing approaches. This section begins by identifying the critical pricing strategy goals. It then formulates price sub-components in-line with these goals before defining the overall pricing functions at increased price space granularity. Lastly, the pricing strategy's case study and simulation process is provided.

### 3.1.5 Exploring Conventional Ethereum Smart Contract Solutions

Smart contracts exhibit desirable properties for energy markets, such as automatic execution, customisation and tamper resistance. The most common smart contract applications have facilitated bidding amounts, determining tariff rates and issuing bills to market participants. However, these are modest applications when considering more advanced bidding strategies. In addition, there is an absence of smart contract simulation approaches in the current literature. Section 3.5 addresses these research gaps by performing an investigative study on the application of Ethereum smart contracts in energy exchanges. This study aims to raise awareness of the practical capabilities of blockchain technology. In this section, an energy ecosystem is identified and modelled into a functional Ethereum-based smart contract. The smart contract is then deployed and evaluated through a blockchain development test network. All steps for this process are provided.

### 3.1.6 Development of a Specialised Peer-to-Peer Blockchain Trading System

There is an increasing demand for global decarbonisation due to environmental concerns. Consequently, the need for localised renewable-based electricity markets is becoming apparent. These markets additionally enhance demand response and operating efficiency through increased market granularity. However, there are concerns about electricity markets being inequitable in market power for all classes of participants. Section 3.6 addresses these concerns by developing a novel blockchain-based market mechanism from the first principles to facilitate energy markets in a decentralised, transparent and secure environment. A case study among three power system stakeholders representing producers, prosumers and consumers is then considered to evaluate the developed system. The market framework, blockchain design process and the simulated energy exchange details are systematically presented in this section.

## 3.2 INVESTIGATING TRADITIONAL ELECTRICITY MARKET APPROACHES

Participant interactions in electricity markets are single-sided or double-sided. Consequently, different approaches are incorporated for determining electricity market prices and participant matches. These approaches are strategically investigated through simulated case studies.

### 3.2.1 Single-sided Electricity Markets

Consider an arbitrary session in a single-sided day-ahead market with sealed bids and energy quantity details as summarised in Table 3.1. The market functions through a conventional uniform price strategy.

**Table 3.1.** Single-sided electricity market requests

| ID | Producer | | Consumer |
|---|---|---|---|
| (Key) | Quantity (kWh) | Price ($\frac{ZAR}{kWh}$) | Demand (kWh) |
| A | 30 | 32 | 24 |
| B | 10 | 10 | 2 |
| C | 25 | 24 | 18 |
| D | 10 | 41 | 31 |
| E | 18 | 36 | 5 |
| F | 15 | 15 | 7 |
| G | 5 | 17 | 8 |
| H | 20 | 28 | - |
| I | 14 | 37 | - |
| J | 16 | 23 | - |

The electricity price is determined through the following steps:

1. Plot the cumulative available electricity quantity for all of the submitted energy offers against the submitted producer offer prices
2. Determine the total required electricity demand for the market session
3. Select the uniform electricity price by finding the corresponding electricity price from the submitted producer offer prices to meet the total demand
4. Schedule the electricity bids according to the prioritisation of the lowest producer offer prices until the demand is met

### 3.2.2 Double-sided Electricity Market

Double-sided electricity markets consider both sides of participants in determining the electricity sale price allowing for more flexible price action. Double-sided markets have two fundamental approaches: market-clearing optimisation and auction-based market clearing. These approaches are considered through a conceptual case study of an arbitrary session in a double-sided electricity market. A summary of electricity offers and bids from producers and consumers is presented in Table 3.2.

**Table 3.2.** Double-sided electricity market requests

| ID | Producer Offers | | Consumer Bids | |
|---|---|---|---|---|
| (Key) | Quantity (kWh) | Price ($\frac{\text{ZAR}}{\text{kWh}}$) | Quantity (kWh) | Price ($\frac{\text{ZAR}}{\text{kWh}}$) |
| A | 30 | 30 | 24 | 20 |
| B | 10 | 10 | 2 | 15 |
| C | 25 | 25 | 18 | 30 |
| D | 10 | 40 | 31 | 25 |
| E | 18 | 35 | 5 | 10 |
| F | 15 | 15 | 7 | 35 |
| G | 5 | 15 | 8 | 5 |
| H | 20 | 30 | - | - |
| I | 14 | 35 | - | - |
| J | 16 | 20 | - | - |

#### 3.2.2.1 Market Clearing Pricing and Scheduling Optimisation

Energy orders can be matched through social welfare optimisation. The optimisation problem definition entails the identification of inputs, decision variables, objective functions and constraints.

Let:

- $N_S \triangleq$ the total number of electrical suppliers
- $j \triangleq$ an arbitrary electricity supplier, where $j = \{1,...,N_S\}$
- $Q_j^S \triangleq$ the maximum electricity quantity (in kWh) on offer for supplier $j$, where $j = \{1,...,N_S\}$
- $\lambda_j^S \triangleq$ the electricity offer price (in $\frac{\text{ZAR}}{\text{kWh}}$) from electricity supplier $j$, where $j = \{1,...,N_S\}$
- $N_C \triangleq$ the total number of electrical consumers
- $i \triangleq$ an arbitrary electricity consumer, where $i = \{1,...,N_C\}$
- $Q_i^C \triangleq$ the maximum electricity quantity (in kWh) on request for consumer $i$, where $i = \{1,...,N_C\}$
- $\lambda_i^C \triangleq$ the electricity bid price (in $\frac{\text{ZAR}}{\text{kWh}}$) from electricity consumer $i$, where $i = \{1,...,N_C\}$
- $y^S \triangleq$ the electricity supply schedule, where $y^S = [y_j^S,...,y_{N_S}^S]^T$
- $y^C \triangleq$ the electricity consumption schedule, where $y^C = [y_i^C,...,y_{N_C}^C]^T$

The optimal social welfare model can then be formulated as follows:

$$\min \quad z = \sum_{j=1}^{N_S} \lambda_j^S y_j^S - \sum_{i=1}^{N_C} \lambda_i^C y_i^C, \tag{3.1}$$

subject to

$$\sum_{j=1}^{N_S} \lambda_j^S y_j^S - \sum_{i=1}^{N_C} \lambda_i^C y_i^C = 0, \tag{3.2}$$

$$0 \leq y_j^S \leq Q_j^S \quad \forall \quad j \in \{1, \ldots, N_S\}, \tag{3.3}$$

$$0 \leq y_i^C \leq Q_i^C \quad \forall \quad i \in \{1, \ldots, N_C\}. \tag{3.4}$$

The objective function in (3.1) optimises social welfare by maximising the signed area between the electricity supply and demand curve. The electricity supply and demand balance requirements are met by (3.2). Finally, the nonnegativity and quantity range of the scheduled quantities is ensured with the introduction of (3.3) and (3.4).

The optimisation problem, defined in (3.1) - (3.4), can then be solved as a linear program (LP) through MATLAB using the *linprog* function to obtain the electricity supply and consumption schedule. Furthermore, the market clearing price can be determined by solving the dual of the LP. A generic LP in compact form is represented by:

$$\min \quad \mathbf{c}^T \mathbf{y}, \tag{3.5}$$

subject to

$$\mathbf{A}\mathbf{y} \leq \mathbf{b}, \tag{3.6}$$

$$\mathbf{A}_{eq}\mathbf{y} = \mathbf{b}_{eq}, \tag{3.7}$$

$$\mathbf{y} \geq 0, \tag{3.8}$$

where $\mathbf{c}$ represents the vector of cost parameters, $\mathbf{y}$ is the vector containing the decision variables, $\mathbf{A}$ and $\mathbf{b}$ represents inequality constraints and $\mathbf{A}_{eq}$ and $\mathbf{b}_{eq}$ represents equality constraints.

The vector of decision variables consists of the generation and consumption schedules and can be represented by:

$$\mathbf{y} = \begin{bmatrix} y_1^S \\ \ldots \\ y_{N_s}^S \\ y_1^C \\ \ldots \\ y_{N_C}^C \end{bmatrix}, \quad \mathbf{y} \in \mathbb{R}^{(N_S+N_C)}. \tag{3.9}$$

The vector of the cost parameters in the optimisation problem correspond to the electricity prices and are represented by:

$$\mathbf{c} = \begin{bmatrix} \lambda_1^S \\ \dots \\ \lambda_{N_s}^S \\ -\lambda_1^C \\ \dots \\ -\lambda_{N_C}^C \end{bmatrix}, \quad \mathbf{c} \in \mathbb{R}^{(N_S+N_C)}. \tag{3.10}$$

The inequality constraints, included in (3.6) maintain electricity balance through predefined limits and are expressed as follows:

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & \dots & \dots & 0 \\ 0 & 0 & 0 & \dots & 1 \end{bmatrix}, \quad \mathbf{A}_{eq} \in \mathbb{R}^{(N_S+N_C)\times(N_S+N_C)}, \tag{3.11}$$

$$\mathbf{b} = \begin{bmatrix} Q_1^S \\ Q_2^S \\ \dots \\ Q_1^C \\ Q_2^C \end{bmatrix}, \quad \mathbf{b}_{eq} \in \mathbb{R}^{(N_S+N_C)}. \tag{3.12}$$

The equality constraints included in (3.7) are defined as follows:

$$\mathbf{A}_{eq} = \begin{bmatrix} 1 & \dots & 1 & -1 & \dots & -1 \end{bmatrix}, \quad \mathbf{A}_{eq} \in \mathbb{R}^{(N_S+N_C)}, \tag{3.13}$$

$$\mathbf{b}_{eq} = 0. \tag{3.14}$$

#### 3.2.2.2 Auction-based Market Clearing

A comprehensive simulation of an auction-based electricity market configuration is performed through MATLAB Simulink. A code block is employed to coordinate the market exchanges according to conventional auction rules. The pseudocode and a simplified configuration overview of the simulation are presented in Fig. 3.1 and 3.2, respectively. This simulation-based approach reduces the computational efforts required to coordinate the participant matching required for a double-sided market. The simulation also provides insight into the market's inner workings, such as participant equity balances and smart grid power flow coordination.

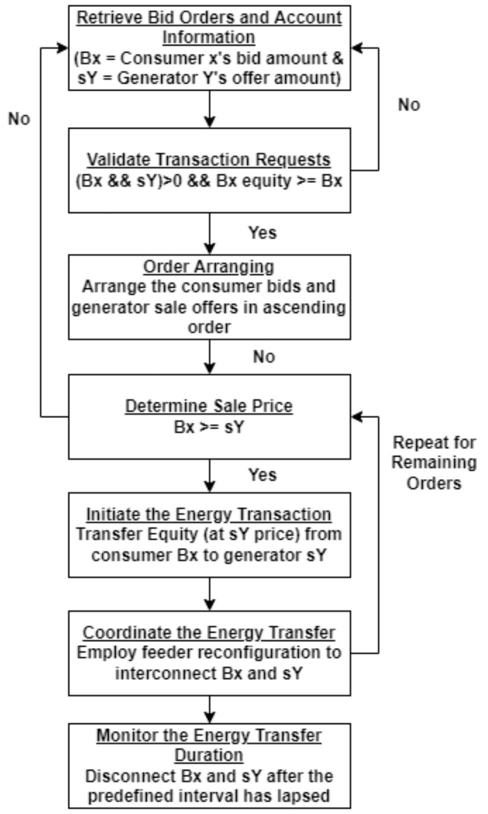



**Figure 3.1.** Psuedocode for auction-based energy market MATLAB Simulink simulation

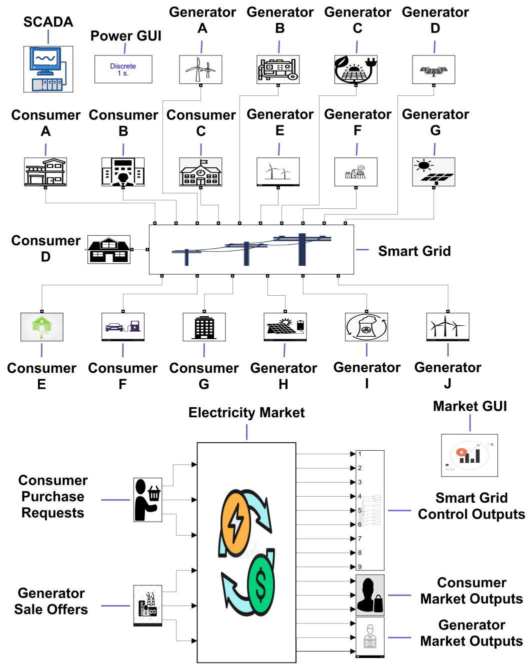



**Figure 3.2.** Configuration overview for auction-based energy market MATLAB Simulink simulation

## 3.3 COMPARISON OF POPULAR MACHINE LEARNING TECHNIQUES FOR SHORT-TERM ENERGY FORECASTING

### 3.3.1 Electricity Demand Forecasting

#### 3.3.1.1 Dataset Background

Actual electricity consumption data for 1 year is selected for this study. The dataset has been provided by PJM Interconnection LLC, a regional transmission organisation in the United States. The organisation serves various parts of the eastern electric transmission system. The dataset is accessible through *Kaggle* [186].

#### 3.3.1.2 Data Loading and Pre-processing

The steps of loading and pre-processing the dataset are as follows:

1. Select the PJME region dataset
2. Upload the dataset into Python IDE
3. Sort the data in terms of ascending date and time order
4. Rename the column variables
5. Perform exploratory data analytics by evaluating the attribute data structures and correlation as summarised in Table 3.3

**Table 3.3.** Exploratory data analytics summary

| Feature | Skewness | Mean | Std | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| Demand ($MW$) | Sym. | 31565.10 | 6608.40 | 19247 | 26823 | 31047 | 34604 | 55934 |

#### 3.3.1.3 Data Cleaning

Data cleaning is performed to handle incomplete data samples and eliminate data errors and redundancy. It contributes to improved data reliability and modelling consistency. The process of data cleaning is as follows:

1. Identify and remove duplicate data
2. Identify incomplete data samples
3. Replace incomplete data samples with linearly interpolated values between existing data samples

#### 3.3.1.4 Feature Engineering

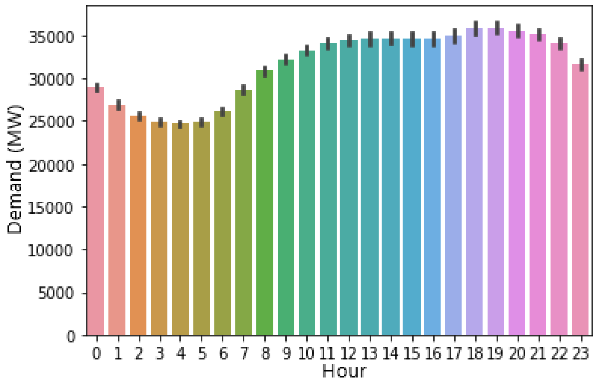
Feature engineering is performed to introduce greater dimensions for the machine learning model, as the present data set consists of raw time stamps and the corresponding electricity demand. Time-related factors influence electricity demand. Consequently, the following features are created through time stamp indexing: hour, day of the week, month, day of the month and season.

#### 3.3.1.5 Feature Analysis

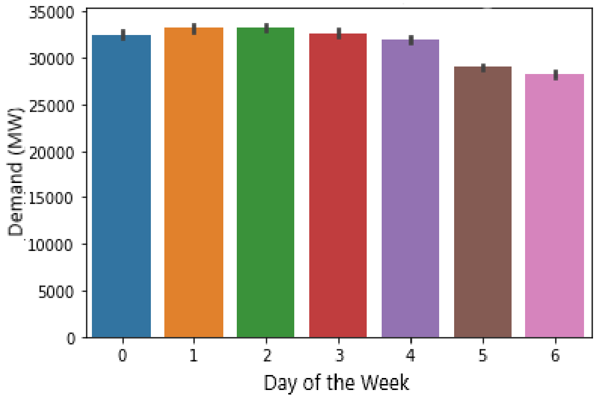
The correlation between electricity demand and the available dataset features is presented in Table 3.4. The *hour* feature exhibits the strongest positive correlation of 0.49. At the same time, the *day of the week* feature has the strongest negative correlation of -0.24. The relationship between the features and the electricity demand is further analysed and confirmed through generated mean load profiles in Fig. 3.3 and 3.4. The monthly interval is overlooked due to limitations on available data.

**Table 3.4.** Correlation between electricity demand and the available dataset features

| Feature | Demand |
|---|---|
| Hour | 0.49 |
| Month | 0.1 |
| Season | 0.06 |
| Day of the Month | -0.04 |
| Day of the Week | -0.24 |

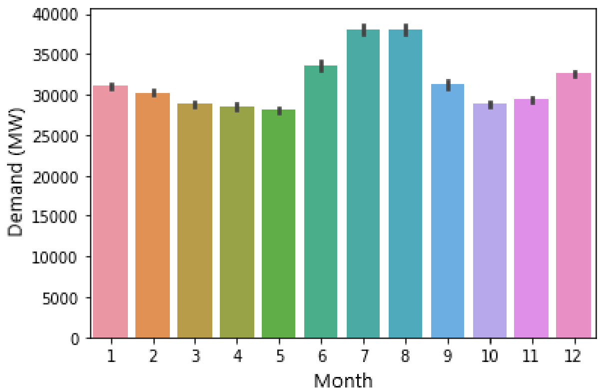



**(a)** Hourly

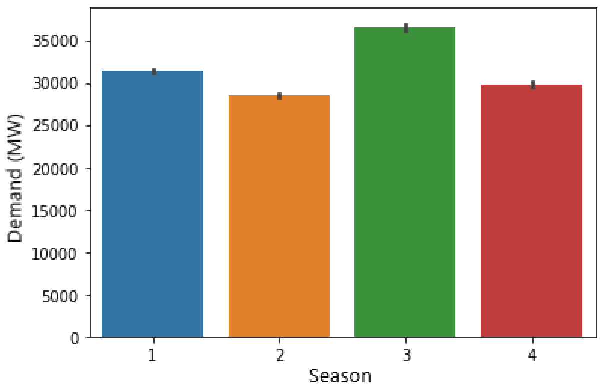



**(b)** Daily

**Figure 3.3.** Mean electricity consumption (MW) across hourly and daily intervals




**(a)** Monthly




**(b)** Seasonal

**Figure 3.4.** Mean electricity consumption (MW) across monthly and seasonal intervals

#### 3.3.1.6 Model Training

The model is trained with 70% of the data serving as the training data set according to standard machine learning practices for smaller data sets. Two subsets of data are used for the model. The first set contains the labelled output data and the second one only contains the selected features. Both data sets are then supplied into various machine learning training algorithms.

#### 3.3.1.7 Model Evaluation

The trained models are examined with the aid of the remaining 30% of the data serving as the test data set. The test data is essential for determining the performance of the trained models as the test data is completely independent of the data used to train the models serving as an impartial test. The models are then evaluated through $R^2$, RMSE and the time taken in training the models.

### 3.3.2 Short Term PV Generation Forecasting

#### 3.3.2.1 Dataset background

Authentic meteorological data from the HI-SEAS weather station is selected for the study. The data has been captured across four months (September - December 2016). The dataset is accessible through *Kaggle* [187].

#### 3.3.2.2 Data Loading and Pre-processing

The steps of loading and pre-processing the dataset are as follows:

1. Upload the HI-SEAS dataset into Python IDE
2. Sort the data in terms of ascending date and time order
3. Rename the column variables
4. Perform exploratory data analytics by evaluating the attribute data structures and correlation as summarised in Table 3.5

**Table 3.5.** Exploratory data analytics summary

| Feature | Skewness | Mean | Std | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|---|
| Radiation ($\frac{W}{m^2}$) | Pos. | 207.12 | 315.92 | 1.11 | 1.23 | 2.66 | 354.24 | 1601.26 |
| Temperature (°F) | Pos. | 51.10 | 6.20 | 34.00 | 46.00 | 50.00 | 55.00 | 71.00 |
| Pressure (Hg) | Sym. | 30.42 | 0.05 | 30.19 | 30.40 | 30.43 | 30.46 | 30.56 |
| Humidity (%) | Neg. | 75.02 | 25.99 | 8.00 | 56.00 | 85.00 | 97.00 | 103.00 |
| Wind Direction (°) | Neg. | 143.49 | 83.17 | 0.09 | 82.23 | 147.70 | 179.31 | 359.95 |
| Wind Speed ($\frac{mi}{s}$) | Pos. | 6.24 | 3.49 | 0.00 | 3.37 | 5.62 | 7.87 | 40.50 |

#### 3.3.2.3 Data Cleaning

Data cleaning is required to ensure the machine learning process is not jeopardised by unnecessary biases in the dataset. It is performed as follows:

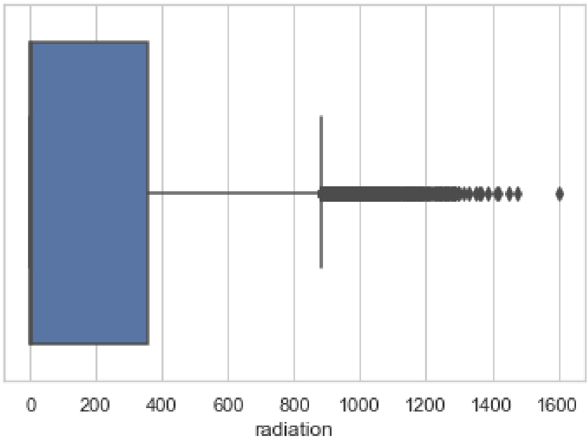
1. Identify if there are null values in the dataset
2. Replace null values through interpolation
3. Identify the presence of outliers
4. Remove any outliers by applying a 1% upper radiation range tolerance as demonstrated in Fig. 3.5.

#### 3.3.2.4 Feature Engineering

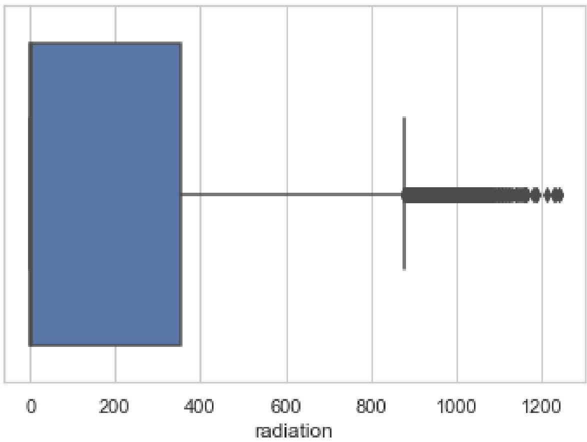
Solar radiation levels are influenced by time-related features which are not explicitly defined in the dataset. As a result, feature engineering is performed through time stamp indexing to introduce other features such as hour and month.

#### 3.3.2.5 Feature Analysis

Feature analysis is performed by identifying the correlations between the available features and solar radiation as summarised in Table 3.6. The *temperature* feature exhibits the strongest positive correlation of 0.73. At the same time, *humidity* and *wind direction* features exhibit the most substantial negative correlations of -0.23. The correlations between the features are further analysed through bar plots. Fig. 3.6 describes the distinct relationship between temperature and solar radiation. It demonstrates that, on average, more elevated temperatures correspond to periods of intenser solar radiation.




**(a)** With outliers




**(b)** Without outliers

**Figure 3.5.** Box plot of solar radiation data ($\frac{\text{W}}{\text{m}^2}$)

**Table 3.6.** Correlation between solar radiation and the available dataset features

| Feature | Radiation |
|---|---|
| Temperature | 0.73 |
| Pressure | 0.12 |
| Wind speed | 0.7 |
| Hour | 0 |
| Month | -0.07 |
| Humidity | -0.23 |
| Wind Direction | -0.23 |

#### 3.3.2.6 Model Training

The model is trained with 70% of the data serving as the training data set according to standard machine learning practices for smaller data sets. Two subsets of data are used for the model. The first set contains the labelled output data and the second one only contains the selected features. Both data sets are then supplied into various machine learning training algorithms.

#### 3.3.2.7 Model Evaluation

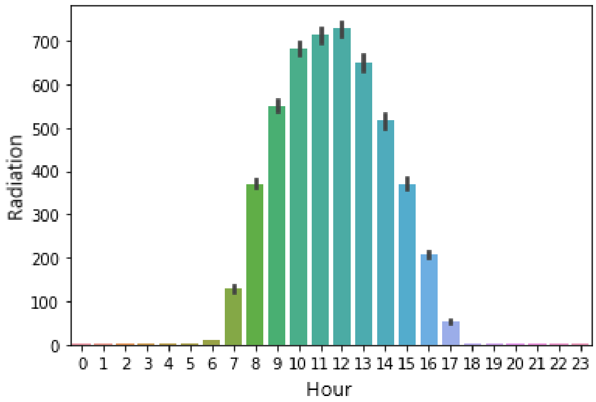
The newly trained models are assessed with the aid of the remaining 30% of the data serving as the test data set. The test data is essential for determining the performance of the trained models as the test data is entirely independent of the data used to train the models serving as an impartial test. The models are then evaluated through $R^2$, RMSE and the time taken in training the models.

## 3.4 PARTICIPANT MATCHING OPTIMISATION IN ELECTRICITY MARKETS

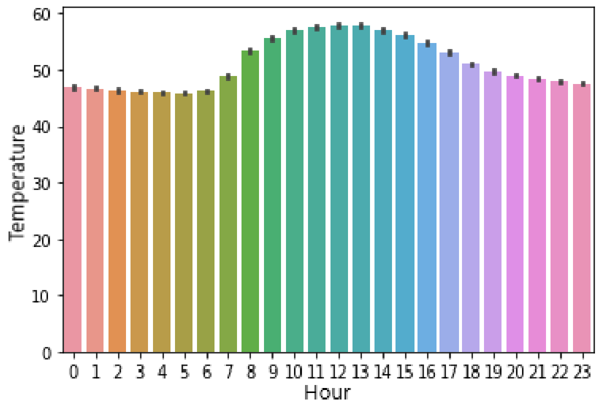
The goal of the participant matching optimisation is to determine the optimal transmission paths for electricity from various market participants to minimise transmission power loss and/or congestion. The optimisation must also account for the electricity demand, baseline transmission congestion, generation capacity and transmission line constraints.

### 3.4.1 Participant Matching Optimisation Model Formulation

Electricity market participant matching can be modelled mathematically to determine optimal bid-matching combinations provided the following assumptions are met:




**(a)** Solar radiation




**(b)** Temperature

**Figure 3.6.** Bar Graphs demonstrating mean solar radiation ($\frac{\text{W}}{\text{m}^2}$) and temperature (°C) by the hour

- Electricity markets are facilitated in smart DC microgrids with a uniform and fixed operational voltage
- Participants submit electricity offers and requests in advance
- Consumers require constant DC power transmission during an arbitrary market session
- Transmission lines have a uniform and constant line resistance per unit
- The capacity ratings of the transmission lines are known
- Baseline levels of transmission congestion can be forecasted and are available

Two objective functions are then modelled. The first model deals with power loss minimisation as the objective function. In comparison, the second model disregards power loss minimisation by modelling transmission congestion as the objective function. The models are then used to form a multi-objective optimisation that will account for both transmission loss and congestion minimisation.

#### 3.4.1.1 Power Loss Objective Modelling

Transmission power loss in DC systems can be represented as:

$$P_l = I^2 dR, \tag{3.15}$$

where $I$ is the current flowing through a transmission line, $d$ is the length of the transmission line and $R$ is the transmission line resistance per unit distance.

At the same time, the transmission line current can be expressed as an expression of power and voltage by:

$$I = \frac{P}{V}, \tag{3.16}$$

where $P$ represents the amount of power transmitted through the transmission line and $V$ is the transmission voltage of the microgrid.

Eq. (3.15) can then be adapted to account for the amount of power transmitted through the substitution of (3.16). The transmission line loss is now represented by the following:

$$P_l = \sum_{n=1}^{E} (\frac{P}{V})^2 dR. \tag{3.17}$$

The total transmission power loss in the power system is then defined by:

$$P_L = \sum_{n=1}^{E} (\frac{P}{V})^2 dR, \tag{3.18}$$

where $E$ is the number of transmission paths.

#### 3.4.1.2 Transmission Congestion Objective Modelling

The total power in a transmission line with baseline congestion and power from an electricity market is expressed by:

$$T_c = P + X, \tag{3.19}$$

where $X$ is the baseline congestion in the transmission line and $P$ is the additional power transmitted from an electricity market.

The relationship in (3.19) is then modelled according to proportionality to capture each variable's influence on the optimisation and result in a more user-friendly objective function. A direct proportionality exists when considering the baseline congestion as a weighting for each transmission path. The modelled weighted transmission congestion parameter is then represented by:

$$T_{c,W} = PX. \tag{3.20}$$

Therefore, the total weighted transmission congestion can be represented by the following:

$$T_C = \sum_{n=1}^{E} T_{c,W}, \tag{3.21}$$

where $E$ is the number of transmission paths.

#### 3.4.1.3 Multi-objective Optimisation Problem Definition

Let:

- $P \triangleq$ the total number of electricity producers
- $C \triangleq$ the total number of electricity consumers
- $i \triangleq$ an arbitrary electricity producer, where $i = \{1,...,P\}$
- $j \triangleq$ an arbitrary electricity consumer, where $j = \{1,...,C\}$
- $d_{ij} \triangleq$ the length of the transmission line (in km) between electricity producer $i$ and electricity consumer $j$, where $i = \{1,...,P\}$ and $j = \{1,...,C\}$
- $R_{ij} \triangleq$ the transmission line resistance (in $\frac{\Omega}{km}$) between electricity producer $i$ and electricity consumer $j$, where $i = \{1,...,P\}$ and $j = \{1,...,C\}$
- $V \triangleq$ the operational voltage of the microgrid
- $x_{ij} \triangleq$ the amount of power (in W) transmitted from electricity producer $i$ to electricity consumer $j$, where $i = \{1,...,P\}$ and $j = \{1,...,C\}$
- $Z_{ij} \triangleq$ the forecasted amount of transmission congestion (in W) between electricity producer $i$ and electricity consumer $j$, where $i = \{1,...,P\}$ and $j = \{1,...,C\}$
- $D_j \triangleq$ the electricity demand (in W) of electricity consumer $j$, where $j = \{1,...,C\}$
- $c_i \triangleq$ the electricity generation capacity (in W) of electricity producer $i$, where $i = \{1,...,P\}$
- $L_{ij} \triangleq$ the transmission line capacity (in W) between electricity producer $i$ and electricity consumer $j$, where $i = \{1,...,P\}$ and $j = \{1,...,C\}$

The problem is then formulated as follows:

$$\min \quad P_L = \sum_{i=1}^{P} \sum_{j=1}^{C} (\frac{x_{ij}}{V})^2 d_{ij} R_{ij}, \tag{3.22}$$

$$\min \quad T_C = \sum_{i=1}^{P} \sum_{j=1}^{C} Z_{ij} x_{ij}, \tag{3.23}$$

subject to

$$\sum_{i=1}^{P} x_{ij} = D_j \quad \forall \quad j \in \{1,...,C\}, \tag{3.24}$$

$$\sum_{j=1}^{C} x_{ij} \leq c_i \quad \forall \quad i \in \{1,...,P\}, \tag{3.25}$$

$$x_{ij} \leq L_{ij} - Z_{ij} \quad \forall \quad i \in \{1,...,P\}, \quad j \in \{1,...,C\}, \tag{3.26}$$

$$x_{ij} \geq 0 \quad \forall \quad i \in \{1,...,P\}, \quad j \in \{1,...,C\}. \tag{3.27}$$

The objective expressed in (3.22) minimises the total transmission power loss. In contrast, the objective expressed in (3.23) minimises the total weighted transmission congestion. Eq. (3.24) is used to ensure that the electricity demand requirements of all consumers are satisfied. Furthermore, the amount of power transferred in the system is restricted to the electricity generation capacity by (3.25). To ensure that the transmission line capacity is not exceeded (3.26) is included, whilst nonnegativity is ensured with (3.27).

### 3.4.2 Participant Matching Optimisation Case Study

#### 3.4.2.1 Scenario

Consider an arbitrary electricity market session in a smart DC microgrid with 7 participants (3 producers and 4 consumers). The electricity offers and requests of the participants are summarised in Tables 3.7 and 3.8, respectively. Furthermore, an overview of the participant transmission distances and baseline congestion is presented in Tables 3.9 and 3.10, respectively. Further information regarding the operational conditions of the microgrid is provided in Table 3.11.

**Table 3.7.** Log of submitted electricity producer offers ($c_i$)

| Producer | Capacity (kW) |
|---|---|
| A | 5 |
| B | 12 |
| C | 9 |

**Table 3.8.** Log of submitted electricity consumer requests ($D_j$)

| Consumer | Demand (kW) |
|---|---|
| a | 6 |
| b | 8 |
| c | 5 |
| d | 3 |

**Table 3.9.** Overview of transmission distances ($D_{i,j}$) between participants (in km)

| Participant | Producer A | Producer B | Producer C |
|---|---|---|---|
| Consumer a | 2 | 25 | 18 |
| Consumer b | 12 | 33 | 30 |
| Consumer c | 25 | 10 | 40 |
| Consumer d | 38 | 9 | 17 |

**Table 3.10.** Overview of forecasted transmission congestion baselines ($X_{i,j}$) between participants (in kW)

| Participant | Producer A | Producer B | Producer C |
|---|---|---|---|
| Consumer a | 0 | 8 | 5 |
| Consumer b | 3 | 6 | 1 |
| Consumer c | 5 | 0 | 7 |
| Consumer d | 6 | 2 | 4 |

**Table 3.11.** Operational information of the microgrid

| Parameter | Value |
|---|---|
| Uniform Operational Voltage ($V$) | 350 V |
| Uniform Transmission Line Power Capacity ($L$) | 17.5 kW |
| Uniform Transmission Line Loss Constant ($R$) | 0.01 $\frac{\Omega}{\text{km}}$ |

#### 3.4.2.2 Optimisation Process

The power loss minimisation objective function described by (3.22) is non-linear. As a result, a non-linear solver in *Microsoft Excel* is used to solve the optimisation problem. Single objective optimisation is considered first to determine the effects of each objective function on the power flow between market participants. Single objective optimisation is performed as follows:

1. Provide the optimisation input variables defined in Tables 3.7 - 3.11
2. Identify the respective decision variables
3. Identify the optimisation limitations
4. Define the constraints in terms of the decision variables
5. Define the expanded total transmission loss objective function as per (3.22)
6. Define the expanded total weighted transmission congestion objective function as per (3.23)
7. Open the *Solver* under *Data*
8. Set the objective function as the expanded total transmission loss defined in Step 5 under *Set Objective*
9. Select the allocated decision variables under *By Changing Variable Cells*
10. Select the objective constraints defined in Steps 3 and 4 under *Subject to Constraints*
11. Enable *Make Unconstrained Variable Non-Negative*
12. Select the solving method as *GRG Nonlinear* under *Select a Solving Method*
13. Click *Solve*
14. Record the optimisation solution
15. Repeat Steps 7 - 12 for the expanded total weighted transmission congestion objective function (defined in Step 6)

The multi-objective optimisation is then solved using preemptive goal programming through the following process:

1. Determine the priority objective function as the first goal
2. Find the optimal values for the first goal
3. Transform the priority objective function as a constraint that will ensure its value remains less or constant

4. Optimise the other objective function whilst enforcing the additional constraint defined in Step 3
5. Record the optimisation solution
6. Repeat Steps 1 - 5 by switching the priority objective functions

## 3.5 A NOVEL APPROACH TO DYNAMIC PRICING IN ELECTRICITY MARKETS

### 3.5.1 Pricing Strategy Goals

The pricing strategy aims to improve the adoption of dynamic pricing in electricity markets. The following serve as goals to realise the aim:

1. Develop a real-time pricing scheme
2. Account for microgrid energy conditions
3. Mitigate price volatility
4. Balance market power
5. Promote demand response
6. Incentivise renewable usage
7. Promote generational capacity investment

### 3.5.2 Factors Considered in the Dynamic Pricing System

#### 3.5.2.1 Demand Response Incentive

Demand response is incentivised by introducing a price component reflective of energy conditions in the microgrid. A combination of short-term machine learning forecasts and real-time analysis of energy conditions is used to increase insight into the system operation and determine appropriate price directions. An overview of price responses to generalised microgrid conditions is presented in Table 3.12. Furthermore, the energy conditions within the DC microgrid can be evaluated through the conservation of energy as represented by:

$$E_{Net} = \sum_{n=1}^{x} E_{Gn} - \sum_{n=1}^{y} E_{Dn} - \sum_{n=1}^{y} E_{Ln}, \tag{3.28}$$

where $E_{Net}$ is the net microgrid energy balance, $E_{Gn}$ is the energy generated at energy supplier $n$, $x$ is the total number of energy suppliers, $E_{Dn}$ is the energy demand consumed by user $n$, $y$ is the total number of energy consumers and $E_{Ln}$ is the energy dissipated in transmitting generated power to the energy consumer $n$.

The demand response price component is designed to be robust to the real-time microgrid energy conditions and is defined by:

$$P_{DR_{ij}} = (\frac{D_j - G_i}{G_i})b \quad \forall \quad i \in \{1, ..., x\}, \quad j \in \{1, ..., y\}, \tag{3.29}$$

where $D_j$ is the real-time electricity demand of Consumer $j$, $G_i$ is the real-time electricity generation capacity of Producer $j$ and $b$ is the base rate of electricity determined from forecasted energy balance conditions.

**Table 3.12.** An overview of price responses to generalised microgrid conditions

| Category | Energy Condition | Price Reaction |
|---|---|---|
| Balanced | $E_{Net} = 0$ | - |
| Surplus | $E_{Net} > 0$ | Lower |
| Deficit | $E_{Net} < 0$ | Higher |

#### 3.5.2.2 Electricity Production Costs

The electricity cost of production is considered in determining the electricity sale price as it significantly influences the generators' profitability. The cost of electricity production depends on the type of generational technology used. Two sub-components of electricity production costs are considered: variable and fixed.

The variable price component varies according to the power generation output levels. The cost of fuel used in electricity production is the dominant expense. However, secondary factors, such as the expense of carbon emission charges, can be included. This price component typically equals zero for renewable energy sources (such as wind and solar). This price component can be described by:

$$P_{VP_i} = P_F \alpha_{G_i} \quad \forall \quad i \in \{1, ..., x\}, \tag{3.30}$$

where $P_F$ is the market price of fuel and $\alpha_{G_i}$ is the fuel consumption rate of electricity Producer $i$.

On the other hand, the fixed price component contains cost factors independent of electricity generation output levels, such as operation and maintenance costs. The average fixed price component is defined by:

$$P_{FP_i} = \frac{T_{M_i} + T_{O_i}}{G_{F_i}} \quad \forall \quad i \in \{1, ..., x\}, \tag{3.31}$$

where $T_{M_i}$ is the total forecasted maintenance costs for Producer $i$, $T_{O_i}$ is the total forecasted operational costs for Producer $i$, and $G_{F_i}$ is the total forecasted electricity generation units for Producer $i$.

#### 3.5.2.3 Transmission Power Loss Costs

Power losses in electricity transmission are considered due to the non-ideal properties of transmission cables. This power component is unused by consumers, but electricity producers supply it. Consumers conventionally incur the costs of transmission line loss. Generators are not charged the transmission line loss costs as it would incentivise price electricity price increments to service these costs. As a result, consumers would still bear the cost of transmission power loss. This challenge can be averted by equally splitting the costs between the consumers and producers as represented by:

$$P_{l_{ij}} = \frac{T_{l_{ij}} P_{E,G_i}}{2} \quad \forall \quad i \in \{1,\ldots,x\}, \quad j \in \{1,\ldots,y\}, \tag{3.32}$$

where $P_{l_{ij}}$ the price component accounting for losses due to electricity transmission between Producer $i$ and Consumer $j$, $T_{l_{ij}}$ is the transmission power lost between Producer $i$ and Consumer $j$ and $P_{E,G_i}$ is the instantaneous price of electricity for Producer $i$.

Eq. (3.32) can be further expanded in terms of the transmitted power by:

$$P_l = \frac{X_{ij}^2 d_{ij} Rij P_{E,G_i}}{2V^2} \quad \forall \quad i \in \{1,\ldots,x\}, \quad j \in \{1,\ldots,y\}, \tag{3.33}$$

where $X_{ij}$ is the power transmitted from Producer $i$ to Consumer $j$, $d_{ij}$ is the length of the transmission line between Producer $i$ and Consumer $j$, $Rij$ is the transmission line resistance per unit distance between Producer $i$ and Consumer $j$ and $V$ is the transmission voltage in the microgrid.

#### 3.5.2.4 Additional Capacity Costs

Transmission congestion is essential when accounting for the network's safe and reliable power flow. During low electricity demands, electricity flow is unconstrained across the grid. Whereas conditions with electricity demand higher than baseline capacity, transmission congestion occurs. As a result, constraints are placed on power flow quantity within the network. Other factors contributing to congestion are the loss of operational power lines or equipment due to maintenance or repair factors. In these cases, additional capacity is recruited. The costs associated with the dispatching of these reserve services are accounted for through the following price component:

$$P_{C_j} = \frac{E_{C_j}}{E_{C,T}} P_{C,T} \quad \forall \quad j \in \{1,\ldots,y\}, \tag{3.34}$$

where $E_{C_j}$ is the additional capacity required for Consumer $j$, $E_{C,T}$ is the total recruited additional capacity and $P_{C,T}$ is the total costs associated with the recruited additional capacity.

#### 3.5.2.5 Price Boundaries/Constraints

Enforcement of electricity price boundaries limits the extent of market price uncertainty. It achieves this by introducing a finite range of possible energy prices, contributing to enhanced predictability and reliability of pricing outcomes.

Dynamic pricing may introduce uncertainty to the potential remuneration benefits for electricity generators from the electricity market. A standardised minimum rate of return is integrated into the dynamic pricing strategy as a lower price boundary to counter this level of uncertainty. This characteristic is achievable by:

$$P_R \leq P_{E,G_i} \quad \forall \quad i \in \{1, \ldots, x\}, \tag{3.35}$$

where $P_R$ is the electricity price corresponding to a predetermined minimum rate of return for electricity generation.

The upper boundary of electricity pricing limits impractical prices, which may occur due to the demand response price component ($P_{DR}$) in high electricity imbalances. The constraint further incentivises consumer participation in the electricity market by ensuring that electricity prices are less than standard utility prices. Consequently, the price of electricity is restricted to the following:

$$P_R \leq P_{E,G_i} < P_{E_T} \quad \forall \quad i \in \{1, \ldots, x\}, \tag{3.36}$$

where $P_{E_T}$ is the standard utility electricity price.

### 3.5.3 Electricity Dynamic Pricing Definition

Specialised price components are defined in (3.29) - (3.36) to account for various price factors such as demand response incentive, electricity production, transmission power loss, additional capacity and price constraints. The integration of these components enables the electricity price to be dynamically determined at increased price granularity.

The real-time electricity remuneration price to arbitrary electricity generators is represented by:

$$P_{E,G}(t) = P_{DR_N}(t) + P_{VP}(t) + P_{FP}(t) - P_l(t), \tag{3.37}$$

subject to

$$P_R(t) \leq P_{E,G}(t) < P_{E_T}(t). \tag{3.38}$$

On the other hand, real-time electricity purchase prices of an arbitrary consumer are represented by:

$$P_{E,C}(t) = P_{DR_N}(t) + P_{VP}(t) + P_{FP}(t) + P_l(t) + P_C(t), \tag{3.39}$$

subject to

$$P_R(t) \leq P_{E,C}(t) - P_{C,C}(t) < P_{E_T}(t). \tag{3.40}$$

### 3.5.4 Case Study

#### 3.5.4.1 Scenario

Consider an arbitrary electricity market in a smart DC microgrid, described by Table 3.13, for three exchange sessions. Each market session consists of hourly forecasts, with pricing updated every 15 minutes according to the proposed dynamic pricing strategy. As a result, there are 4 price iterations every session. The demand response base rates are determined according to the extent of energy condition imbalances and are summarised in Table 3.14. In addition, the final producer electricity prices in the market are limited to 0.0002 - 0.002 $\frac{\text{ZAR}}{\text{W}}$.

Three electricity producers (A-C) and three consumers (1 -3) are considered in this case study. Producer A operates a diesel generation, Producer B uses a wind turbine and Producer C has a solar PV system to generate electricity. Additional market generation support is available through standby diesel generators in cases where demand response is insufficient. These generators are dispatched at a 10% markup to the market fuel price. The fuel market price is assumed to be 20 $\frac{\text{ZAR}}{\text{l}}$. An overview of the transmission distance between the market participants is described in Table 3.15. Hour-ahead energy generation and demand forecasts for each participant are presented in Tables 3.16 and 3.17. Real-time samples of the electricity demand are taken every 15 minutes and are summarised in Tables 3.18 - 3.20. Furthermore, each producer's fixed costs (maintenance and operation costs) are summarised in 3.21. Lastly, the fuel consumptions of the electricity producers are provided in Table 3.22.

**Table 3.13.** Operational information of the Microgrid

| Parameter | Value |
|---|---|
| Uniform Operational Voltage | 350 V |
| Uniform Transmission Line Power Capacity | 17.5 kW |
| Uniform Transmission Line Loss Constant | 0.01 $\frac{\Omega}{\text{km}}$ |
| Reserve Capacity Generator Fuel Consumption | 0.00005 $\frac{\text{l}}{\text{W}}$ |

**Table 3.14.** Baseline demand response price coefficients ($\frac{\text{ZAR}}{\text{W}}$)

| Energy Imbalance (%) | Baseline |
|---|---|
| 0.1 - 2.5 | 2.5 |
| 2.5 - 5 | 3.33 |
| 5 - 7.5 | 4.17 |
| 7.5 - 10 | 5 |
| 10 - 12.5 | 5.83 |

**Table 3.15.** Overview of transmission distances (in km) between participants

| Participant | Producer A | Producer B | Producer C |
|---|---|---|---|
| Consumer 1 | 5 | 2 | 8 |
| Consumer 2 | 1 | 6 | 10 |
| Consumer 3 | 9 | 2 | 1 |

**Table 3.16.** Forecasted electricity producer capacity (in W)

| Producer | Session 1 | Session 2 | Session 3 |
|---|---|---|---|
| A | 4050 | 3000 | 4950 |
| B | 3500 | 1000 | 4750 |
| C | 2200 | 4000 | 3000 |

**Table 3.17.** Forecasted electricity consumer demand (in W)

| Consumer | Session 1 | Session 2 | Session 3 |
|---|---|---|---|
| 1 | 3000 | 1000 | 5000 |
| 2 | 4000 | 3000 | 5000 |
| 3 | 2000 | 4000 | 3000 |

**Table 3.18.** Real-time electricity consumer demand (in W) for session 1

| Consumer | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| 1 | 2975 | 2985 | 2920 | 2950 |
| 2 | 3915 | 3965 | 3910 | 3935 |
| 3 | 1910 | 1940 | 2000 | 1940 |

**Table 3.19.** Real-time electricity consumer demand (in W) for session 2

| Consumer | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| 1 | 1000 | 1000 | 1000 | 1000 |
| 2 | 3000 | 3000 | 3000 | 3000 |
| 3 | 4000 | 4000 | 4000 | 4000 |

**Table 3.20.** Real-time electricity consumer demand (in W) for session 3

| Consumer | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| 1 | 5020 | 5025 | 5040 | 5090 |
| 2 | 5060 | 5085 | 5010 | 5045 |
| 3 | 3080 | 3080 | 3030 | 3005 |

**Table 3.21.** Producer fixed cost rates ($\frac{\text{ZAR}}{\text{W}}$)

| Producer | Maintenance | Operation |
|---|---|---|
| A | 0.0005 | 0.00025 |
| B | 0.00075 | 0 |
| C | 0 | 0 |

**Table 3.22.** Producer generator fuel consumption ($\frac{1}{\mathrm{W}}$)

| Producer | Maintenance |
|---|---|
| A | 0.00005 |
| B | 0 |
| C | 0 |

#### 3.5.4.2 Simulation

The dynamic pricing case study is modelled in Matlab Simulink using various components as depicted in Fig. 3.7. The simulation consists of software and hardware modelling.

The software aspect is considered first with a *Matlab Function* component used to facilitate the dynamic pricing strategy through computational logic. Pricing inputs, such as forecasts and real-time data samples, are provided to the algorithm through *Repeating Sequence Stair* components. The software defines other inputs from the case study, such as transmission distances and price coefficients. The proposed dynamic pricing algorithm's pseudocode is provided in Fig. 3.8. Outputs from the *Matlab Function* component are then distributed through *Go To* components for the more precise organisation of the simulation. This approach enables the bridging between the software and hardware elements. Two classes of algorithm outputs exist. The first class of algorithm outputs consists of the digital signal that controls the smart distribution system between market participants. On the other hand, the second class of algorithm outputs represent the specialised electricity prices for each participant.

The hardware aspect consists of the smart distribution system, producer generators, consumer loads and graphical user interface. The smart distribution system is modelled through *Ideal Switch* components with the control input received through *From* components. These *From* components are associated with the *Go To* components in the software area of the simulation. As a result, the distribution system is directly controlled by the algorithm. Power generators are modelled individually through *Battery* components to provide constant power. Whereas consumer loads are modelled through *Variable Resistor* components with resistances varied through *Repeating Sequence Stair* components. This model enables the capturing of the real-time dynamic nature of electrical demands. Lastly, real-time power measurements and price reflections are provided through *Scope* components.

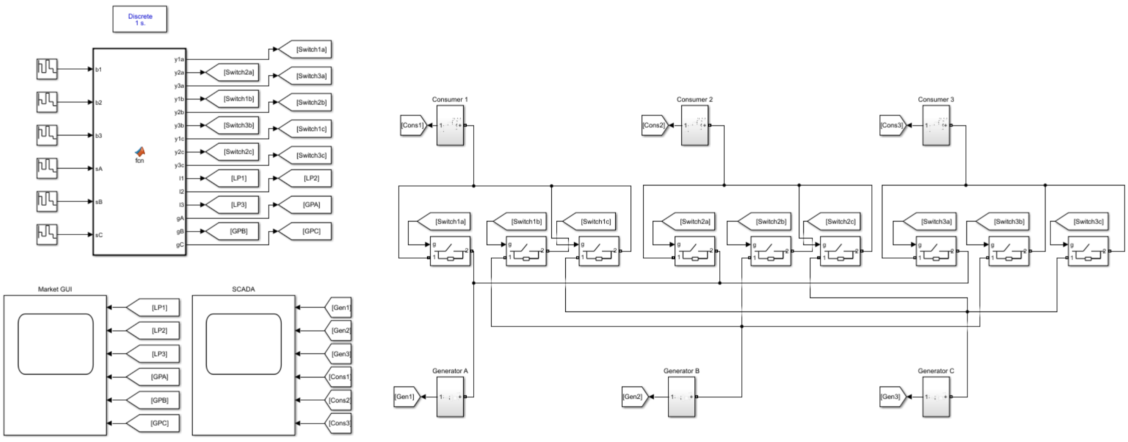



**Figure 3.7.** MATLAB Simulink dynamic pricing case study simulation model

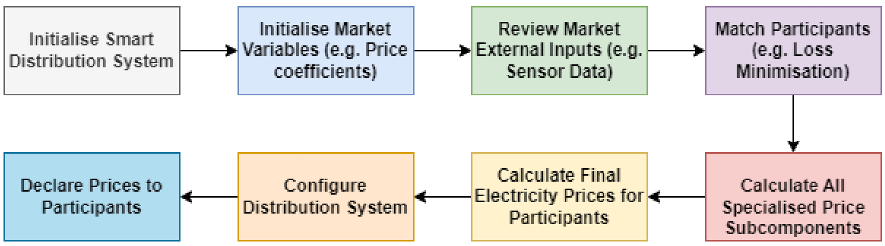



**Figure 3.8.** Pricing strategy simulation algorithm psuedocode

## 3.6 EXPLORING CONVENTIONAL ETHEREUM SMART CONTRACT SOLUTIONS

The application of decentralised and localised energy markets can increase the viability of power networks by promoting active demand management and localised energy generation by energy ecosystem users. A few key advantages arise from this approach, such as load profile flattening, improved power stability, increased renewable energy penetration and enhanced power system reliability.

The potential for energy market adoption can drastically be improved by representing stored electrical energy (ePower tokens) and the local currency (eZAR tokens) in digital form. Furthermore, there are intrinsic requirements of trust, computational logic and automatic execution of localised energy exchanges. The application of smart contracts in energy token exchanges is proposed to cater for these requirements.

### 3.6.1 Digital Energy Ecosystem

Energy markets are traditionally facilitated through intermediary energy exchange platforms, which are centralised [188]. Smart contracts are attractive replacements for energy exchanges that can serve as a transparent and impartial intermediary between participants [189, 190]. These contracts are defined using computational logic to coordinate energy exchange transactions autonomously and reliably [191]. Before smart contract technology can be integrated, energy markets must first be represented in the digital domain. One approach taken is by representing stored energy units and the local currency as cryptoassets/tokens [192]. A protocol token, referred to as ePower, is being used to represent 100 Wh of energy. On the other hand, the local currency is represented by a stablecoin represented by eZAR. The value of eZAR is dictated by the underlying local currency of South Africa (ZAR). For this study, ePower has been selected to have an exchange rate represented by:

$$1 \quad \text{eZAR} = 10 \quad \text{ePower}. \tag{3.41}$$

An energy market among three parties (producer, consumer and prosumer) has been selected for exploration as each party represents a fundamental user in an advanced energy ecosystem. Each party has initial equity balances as described by Table 3.23. The following transactions are considered:

1. The energy prosumer purchases ePower tokens to the value of 500 eZAR from the energy producer.
2. The energy prosumer sells 1500 ePower tokens to the energy producer.
3. The energy consumer purchases ePower tokens to the value of 200 eZAR from the energy producer.

**Table 3.23.** Initialised equity balances in the energy ecosystem

| Producer | | Prosumer | | Consumer | |
|---|---|---|---|---|---|
| eZAR | ePower | eZAR | ePower | eZAR | ePower |
| 0 | 10000 | 1000 | 0 | 1000 | 0 |

### 3.6.2 Smart Contract Creation

#### 3.6.2.1 Agreement Modelling

Various energy token exchange scenarios can be modelled as a traditional contract using the framework presented in Fig. 3.9.


**Figure 3.9.** Energy exchange elements modelled through a proposed framework

#### 3.6.2.2 Smart Contract Definition

The standard contract terms can be integrated into a Solidity program [193] compiled on an open-source online integrated development environment (IDE) such as Remix. Diverse program elements [194] are presented in a single collection of code and data known as the ePower market. An overview of the smart contract's components is presented in Fig. 3.10. Further details of the smart contract definition process are provided in Fig. 3.11.

### 3.6.3 Smart Contract Deployment

Ganache truffle suite [195] has been employed for blockchain development on an Ethereum test network. The system provides a user interface capable of interacting with the entire life cycle of a smart contract. MyEtherWallet, an open-source user interface, is then employed to interact directly with the virtual Ethereum network [196]. The interface requires a communication link with the blockchain, which can be obtained by creating a custom node on MyEtherWallet containing the RPC Server and Network ID of the workstation configured in Ganache. Once the node has been configured, the smart

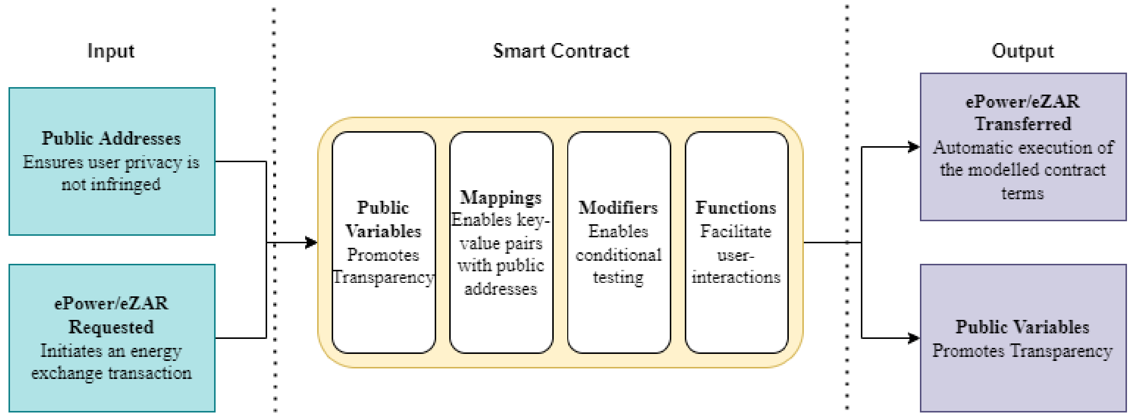



**Figure 3.10.** Representation of the smart contract as a multiple-input multiple-output system

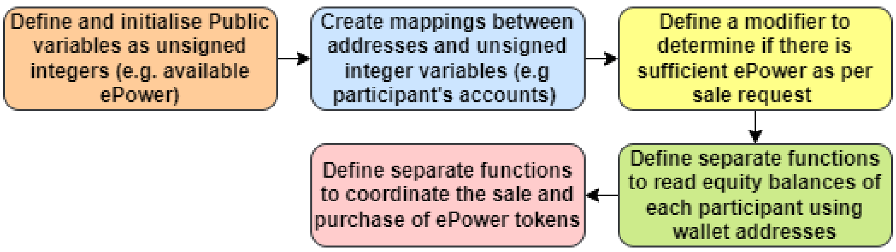



**Figure 3.11.** Overview of the smart contract definition process

contract can be transformed into the byte code equivalent with the aid of Remix IDE. The registered energy producer has been selected to sign the smart contract with the aid of their private key. As a result, this participant incurs an expense, known as a gas fee, to deploy the contract on the Ethereum blockchain.

### 3.6.4 Smart Contract Interaction

The energy ecosystem case study is then simulated by interacting with the deployed smart contract through read or write commands via MyEtherWallet with an overview of all completed energy exchange transactions depicted in Fig. 4.6.

## 3.7 DEVELOPMENT OF A SPECIALISED PEER-TO-PEER BLOCKCHAIN TRADING SYSTEM

Peer-to-peer (P2P) energy trading enables greater user involvement in power systems by transforming the role of traditional end consumers from passive to active network managers. This strategy offers a more feasible approach to energy management by enhancing grid reinforcements through distributed energy generation. Additional benefits of this approach include increased renewable energy penetration,

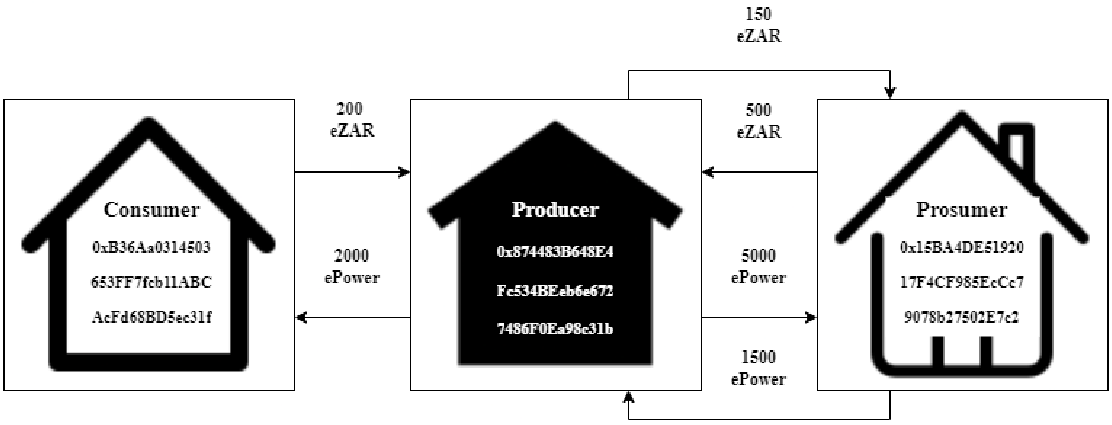



**Figure 3.12.** The energy ecosystem considered in this study

improved energy accessibility, greater power system reliability and energy congestion management. A specialised blockchain system is developed to autonomously manage energy exchanges among three categories of power system stakeholders (producers, prosumers and consumers) in a decentralised and regulated manner.

### 3.7.1 Smart Contract Modelling

The terms of the energy market can be identified by modelling various energy token exchange scenarios as traditional contracts between network users. Energy exchange can be represented in the digital domain by representing stored energy units and the local currency as crypto asset tokens. A protocol token, referred to as ePower, is used to represent stored energy with an exchange rate described by:

$$1 \quad \text{ePower} = 0.1 \quad \text{kWh}. \tag{3.42}$$

On the other hand, the local currency is represented by a stablecoin represented by eZAR. The value of eZAR is dictated by the underlying local currency of South Africa (ZAR). For this study, ePower has been selected to have an exchange rate represented by:

$$1 \quad \text{eZAR} = 10 \quad \text{ePower}. \tag{3.43}$$

Ensuring optimal power quality in a power system is of paramount importance as it influences the functionality of the end user's equipment and loads. Four critical aspects are related to power quality: harmonics, voltage dips, voltage unbalance and voltage flicker. Due to the direct current (DC) operation assumption, voltage unbalance will not be considered. A simplified example of the smart contract framework regulating the issuing of energy crypto assets is presented in Fig. 3.13. Furthermore, the framework proposed in Fig. 3.9 is used to coordinate energy exchanges between two participants.

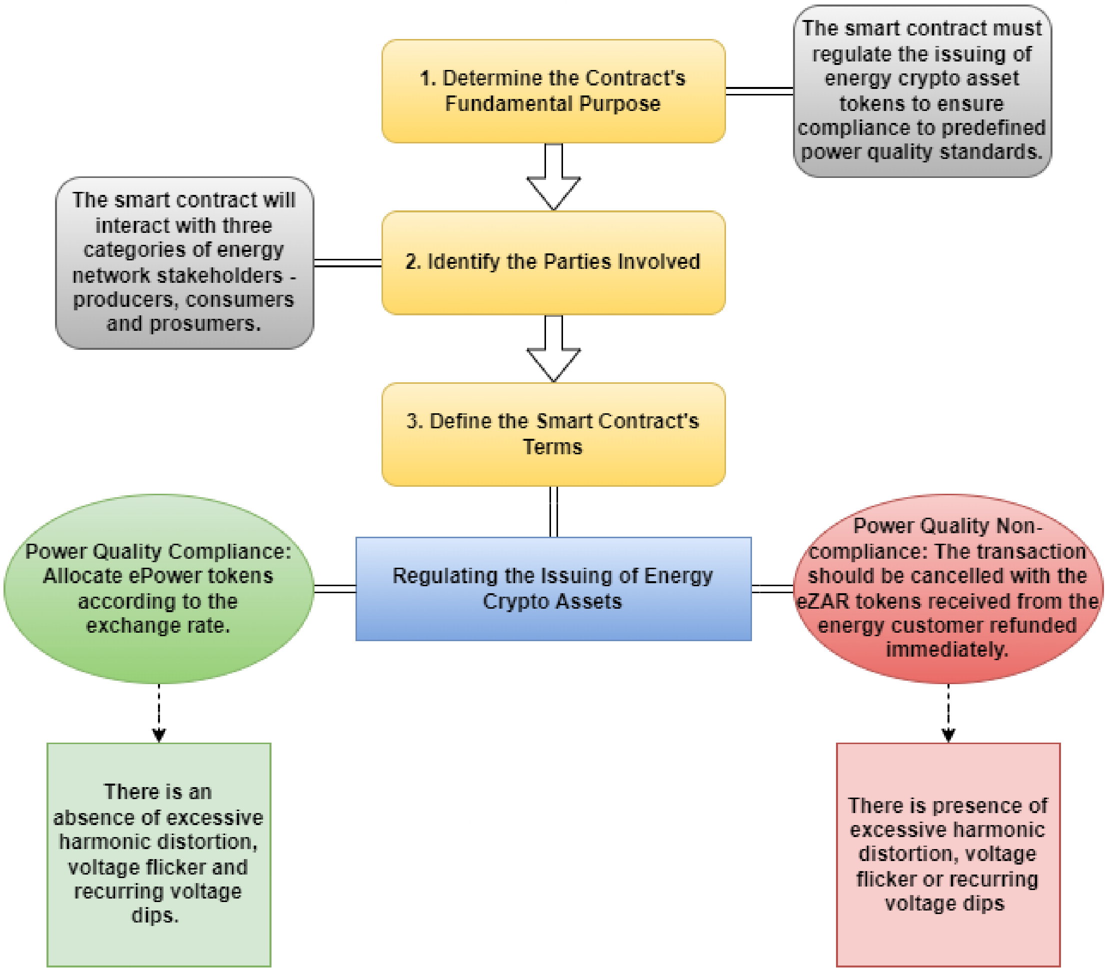



**Figure 3.13.** A simplified example of the smart contract framework regulating the issuing of energy crypto assets

### 3.7.2 Peer-to-Peer Energy Trading System Development

A blockchain is a distributed data ledger consisting of individual ledgers (represented by blocks) interlinked through cryptography (represented as chains) [197]. These properties enable blockchains to be characterised as reliable, immutable, and transparent.

Python has been selected as the programming language for the system implementation as it can be operated on various operating systems. Furthermore, an object-orientated programming approach has been used to promote modularity and flexibility of the software for debugging and future improvements.

#### 3.7.2.1 Blockchain Definition

The blockchain is defined as a class containing objects and object methods with specialised features derived from the first principles. An overview of the functions of each object method is presented in Fig. 3.14.

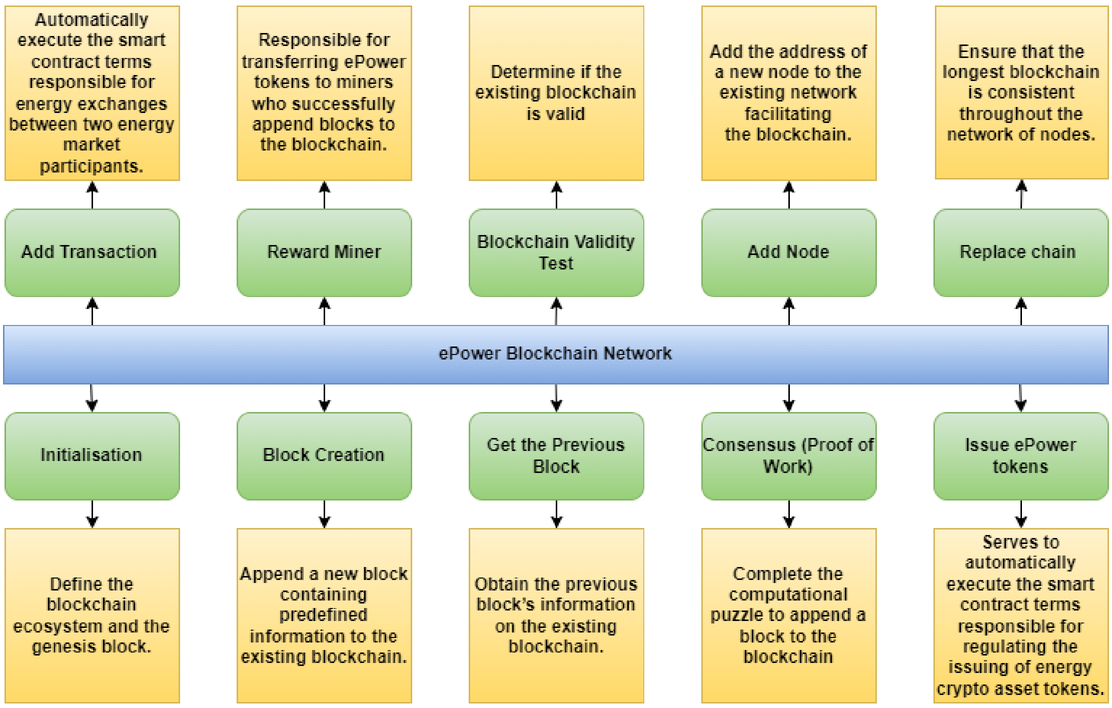



**Figure 3.14.** Overview of the functions of each object method

#### 3.7.2.2 Block Mining

Block mining incorporates the object methods defined for the blockchain. Each node in the blockchain network will compete to solve the computational puzzle defined in the Proof of Work (PoW) algorithm. The node that obtains the proof hash first qualifies to mine a block. In doing so, miners retrieve an automatic transaction reward (gas) as ePower tokens. This incentive-based strategy enhances the reliability and security of the blockchain. The block mining process is depicted in Fig. 3.15 and is contained in a single function.

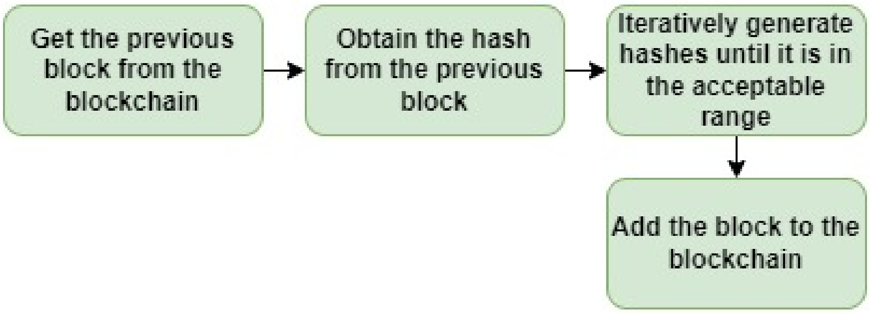



**Figure 3.15.** Mining Process followed to add a block to the blockchain

#### 3.7.2.3 Network Synchronisation

Decentralisation of the system can be achieved by interconnecting distributed nodes into an existing blockchain network. The node information can be retrieved in the parsed uniform resource locator (URL) format. Synchronisation is determined by comparing individual nodes' stored chains with other chains retrieved, as depicted in Fig. 3.16. Synchronisation favours the longest chain as this is the most secure version with the most historical data. Shorter chains are disregarded.

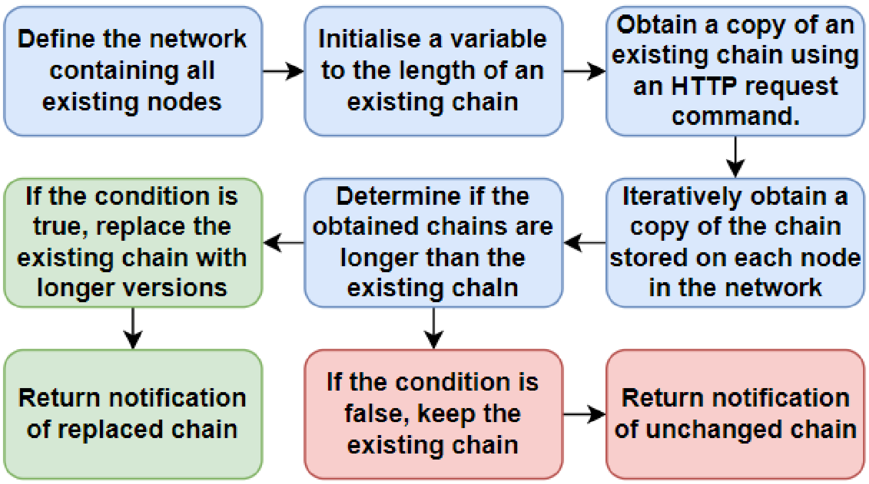



**Figure 3.16.** Process followed when initiating a chain synchronisation request

#### 3.7.2.4 Regulating the Issuing of Crypto Assets

Crypto asset issuing is regulated through a specific function encoded on the blockchain network. The function requires the submission of an energy quality report by registered energy generators/prosumers who would like to sell energy on the market. The system audits the report according to hard-coded criteria in the form of a smart contract and acts accordingly. An overview of the smart contract regulating the issuing of crypto assets is presented in Fig. 3.17.

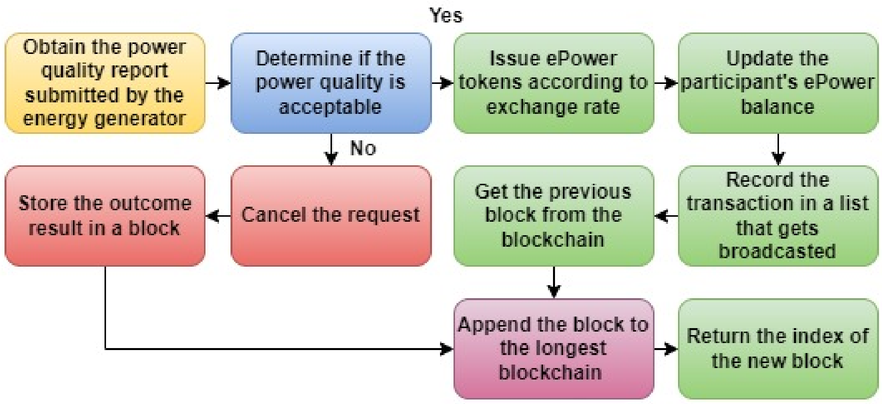



**Figure 3.17.** Overview of the function regulating the issuing of crypto assets

#### 3.7.2.5 Coordinating token exchanges

Similar to the smart contract feature regulating the issuing of crypto assets on the ePower network, a specialised function is developed to coordinate token exchanges. This process is depicted in Fig. 3.18. The exchange process is designed to autonomously execute when participants initiate transaction requests.

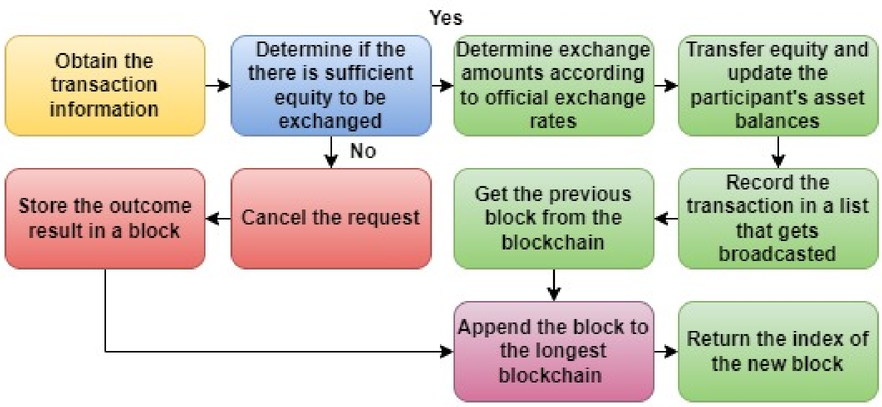



**Figure 3.18.** Overview of the function coordinating token exchanges among market participants

#### 3.7.2.6 User Interface

A user interface is facilitated through Flask. Flask is a web framework that enables interaction with the Blockchain network by implementing Hypertext Transfer Protocol (HTTP) methods and routes in three server algorithms. Each hosted server represents a different node in the network and is operated through individual console tabs on Spyder. HTTP GET request methods are employed to retrieve information from servers hosted by the decentralised network of nodes. HTTP POST request methods are employed to send information in the form of JavaScript Object Notation (JSON) files to the blockchain servers. An overview of the process followed when configuring the website application is presented in Fig. 3.19.

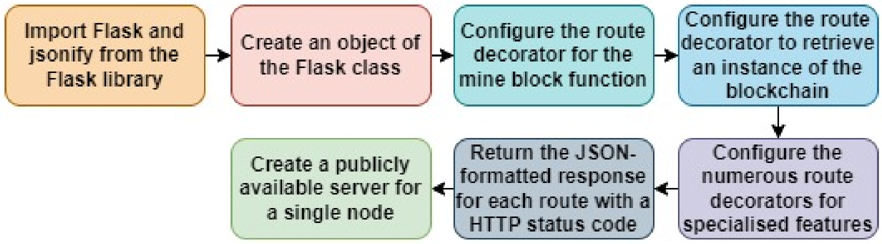



**Figure 3.19.** Process followed when configuring the website application

### 3.7.3 Energy Exchange

#### 3.7.3.1 Energy Transactions

An energy exchange among three parties (producer, consumer and prosumer) is selected for exploration. Each party represents a fundamental user in an advanced energy ecosystem. The following transactions are considered:

1. The energy producer submits a report containing compliant outcomes for various power quality criteria (absence of voltage flicker, voltage dips and harmonic distortion) requesting the issuing of ePower tokens for 2000 kWh of stored energy.
2. The energy consumer submits a request to purchase 5000 ePower tokens (equivalent to 500 kWh) from the energy producer.
3. The energy prosumer submits a report containing compliant outcomes for various power quality criteria (absence of voltage flicker, voltage dips and harmonic distortion) requesting the issuing of ePower tokens for 250 kWh of excess stored energy.
4. The energy prosumer submits a request to purchase 3000 ePower tokens (equivalent to 300 kWh) from the energy producer.
5. The energy consumer submits a request to purchase 1000 ePower tokens (equivalent to 100 kWh) from the energy prosumer.
6. The energy producer submits a report containing compliant and non-compliant outcomes for various power quality criteria (absence of voltage flicker and voltage dips with the presence of excessive harmonic distortion) requesting the issuing of ePower tokens for 500 kWh of stored energy.

7. The energy prosumer submits a request to purchase 12500 ePower tokens (equivalent to 1250 kWh) from the energy producer.

In addition to the selected transactions, parameters such as initial equity balances are initialised as summarised in Table 3.24.

**Table 3.24.** Initialised parameters in the simulated exchange

| Parameter | Value |
|---|---|
| Exchange Rate ($\frac{\text{ePower}}{\text{eZAR}}$) | 10 |
| Producer eZAR | 0 |
| Producer ePower | 0 |
| Prosumer eZAR | 1500 |
| Prosumer ePower | 0 |
| Consumer eZAR | 1000 |
| Consumer ePower | 0 |

# CHAPTER 4 RESULTS FROM THE PROPOSED ELECTRICITY MARKET SYSTEM

## 4.1 CHAPTER OVERVIEW

This chapter sets out to present the results and observations of conducted experiments. An overview of each section is provided as follows:

### 4.1.1 Investigating Traditional Electricity Market Approaches

Section 4.2 presents the results of different pricing and participant matching strategies for various electricity market case studies. The case studies considered include single-sided and double-sided markets. Furthermore, the resultant electricity prices and the energy exchange schedules for each investigated configuration are tabulated on a per-session basis for ease of interpretation.

### 4.1.2 Comparison of Popular Machine Learning Techniques for Short-Term Energy Forecasting

Section 4.3 presents the performance results for 42 machine learning models for short-term electricity demand and solar radiance forecasting. The parameters presented are R-score, RMSE and the time to train each model. These parameters provide insight into the accuracy and efficiency of each training algorithm. Furthermore, the results are tabulated from lowest RMSE to highest RMSE to identify the top-performing models for the considered applications.

### 4.1.3 Participant Matching Optimisation in Electricity Markets

Section 4.4 presents the optimisation results of the considered case study from single-objective and multi-objective perspectives. The results include tabulated power flows (including and excluding baseline transmission congestion) among all market participants and the total electricity quantity schedule. In addition, the total transmission losses and weighted congestion values are provided to enable efficient comparisons of each approach. Furthermore, the transmission loss and congestion minimisation results are presented independently for ease of interpretation. Similarly, the solutions for the preemptive multi-objective problems are provided separately.

### 4.1.4 A Novel Approach to Dynamic Pricing in Electricity Markets

Section 4.5 contains the results from a simulated DC microgrid electricity market case study using a novel dynamic pricing strategy. The electricity prices are presented for each market participant in tabulated form with sub-price components also included. This presentation approach enables an overview of the adaptability and efficiency of the proposed strategy for varying market conditions. Furthermore, the inclusion of the subcomponent prices enables the evaluation of their impact on the overall electricity price under different circumstances.

### 4.1.5 Exploring Conventional Smart Contract Solutions

Section 4.6 presents the results from the deployed Ethereum smart contract. Extracts of the available smart contract features and user interfaces are provided for additional insight into the capabilities of the approach. Furthermore, the complete Ethereum blockchain, after completing the simulated transactions, is included to highlight the gas fees associated with each stage of the smart contract's life cycle. Lastly, a summary of all reflected account balances for each transaction is provided.

### 4.1.6 Development of a Specialised Peer-to-Peer Blockchain Trading System

Section 4.7 presents the results of several electricity exchange transactions for various energy balance and power quality conditions simulated on the developed blockchain network consisting of three independent nodes. It accomplishes this by providing extracts of the blockchain ledger and participant user interfaces. Lastly, summaries of the final account balances of the electricity market's participants are tabulated.

## 4.2 INVESTIGATING TRADITIONAL ELECTRICITY MARKET APPROACHES

### 4.2.1 Single-sided Electricity Market

The uniform electricity price corresponds to 32 $\frac{\text{ZAR}}{\text{kWh}}$ when catering for a total electricity demand of 95 kWh, as presented in Fig. 4.1. Furthermore, the energy exchange schedule to meet the total demand is provided in Table 4.1. Lastly, a summary of the unsold electricity offers is included in Table 4.2.

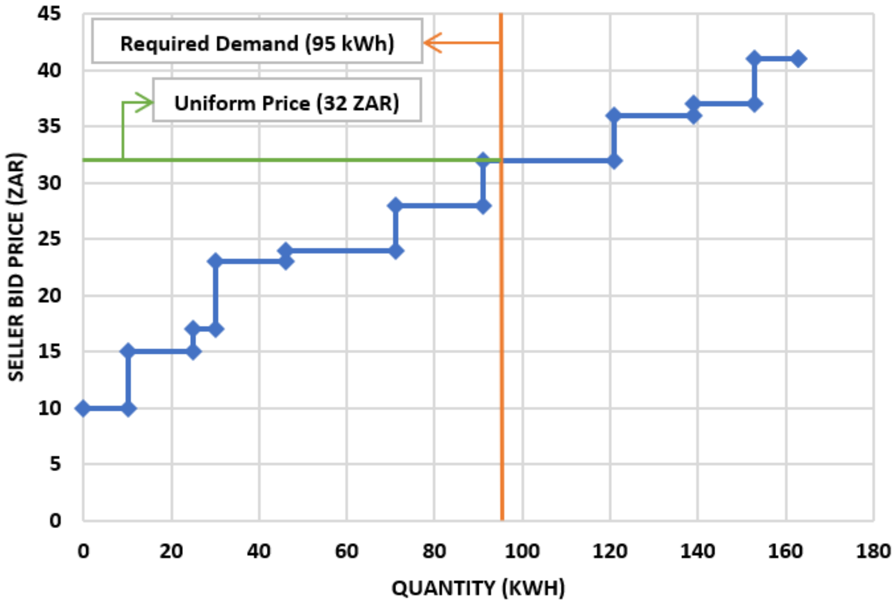



**Figure 4.1.** Uniform price selection in a single-sided electricity market for an arbitrary session

**Table 4.1.** Day-ahead market electricity schedule

| ID | Producer Quantity (kWh) | Consumer Quantity (kWh) |
|---|---|---|
| A | 4 | 24 |
| B | 10 | 2 |
| C | 25 | 18 |
| D | - | 31 |
| E | - | 5 |
| F | 15 | 7 |
| G | 5 | 8 |
| H | 20 | - |
| I | - | - |
| J | 16 | - |

**Table 4.2.** Unsold electricity offers from the single-sided electricity market

| ID | Unsold Quantity (kWh) |
|---|---|
| A | 26 |
| D | 10 |
| E | 18 |
| I | 14 |

### 4.2.2 Double-sided Electricity Markets

#### 4.2.2.1 Market Clearing Pricing and Scheduling Optimisation

Solving the formulated LP results in the electricity generation and consumption schedules portrayed in Table 4.3. However, the optimisation does result in unsold electricity as summarised in Table 4.4. Furthermore, the optimal market clearing price is determined to be 30 $\frac{\text{ZAR}}{\text{kWh}}$.

**Table 4.3.** Electricity MCP market schedule

| ID | Producer Quantity (kWh) | Consumer Quantity (kWh) |
|---|---|---|
| A | 24 | 24 |
| B | 10 | 2 |
| C | 25 | 18 |
| D | - | 31 |
| E | - | 5 |
| F | 15 | 7 |
| G | 5 | 8 |
| H | - | - |
| I | - | - |
| J | 16 | - |

**Table 4.4.** Unsold electricity offers from MCP optimisation

| ID | Unsold Quantity (kWh) |
|---|---|
| A | 6 |
| D | 10 |
| E | 18 |
| H | 20 |
| I | 14 |

#### 4.2.2.2 Auction-based Approach

The auction-based approach results in various market clearing prices and quantities as summarised in Table 4.5. The electricity market schedule provides insight into matched participants, approved energy quantities and the electricity sale price. Furthermore, all unmatched market orders are summarised in Table 4.6.

**Table 4.5.** Auction-based electricity market schedule

| Producer ID | Consumer ID | Quantity (kWh) | Clearing Price ($\frac{\text{ZAR}}{\text{kWh}}$) |
|---|---|---|---|
| A | C | 18 | 30 |
| B | E | 5 | 10 |
| C | D | 25 | 25 |
| D | - | - | - |
| E | F | 7 | 35 |
| F | A | 14 | 15 |
| F | B | 1 | 15 |
| G | B | 1 | 15 |
| H | - | - | - |
| I | - | - | - |
| J | D | 6 | 20 |
| J | A | 10 | 20 |

**Table 4.6.** Unmatched orders from auction-based electricity market

| ID | Unsold Producer Quantity (kWh) | Unfilled Consumer Quantity (kWh) |
|---|---|---|
| A | 12 | - |
| B | 5 | - |
| D | 10 | - |
| E | 11 | - |
| F | 10 | - |
| G | 4 | 8 |
| H | 20 | - |
| I | 14 | - |

## 4.3 COMPARISON OF POPULAR MACHINE LEARNING TECHNIQUES FOR SHORT-TERM ENERGY FORECASTING

### 4.3.1 Electricity Demand

The performance attributes of the investigated machine learning algorithms for short-term solar radiance forecasting are summarised in Tables 4.7 - 4.9 in order of ascending RMSE.

**Table 4.7.** Performance attributes of the selected electricity demand model parameters under various machine learning algorithms 1

| Algorithm | R-Squared | RMSE (MW) | Training Time (s) |
|---|---|---|---|
| Extreme Gradient Boosting Regressor | 0.98 | 833.32 | 0.23 |
| Random Forest Regressor | 0.97 | 1179.63 | 0.98 |
| Bagging Regressor | 0.96 | 1255.46 | 0.11 |
| Extra Trees Regressor | 0.96 | 1308.96 | 0.93 |
| Light Gradient Boosted Machine Regressor | 0.96 | 1326.04 | 0.09 |
| Histogram Gradient Boosting Regressor | 0.96 | 1326.04 | 0.51 |
| Decision Tree Regressor | 0.95 | 1541.12 | 0.02 |
| Gaussian Process Regressor | 0.93 | 1737.80 | 4.88 |
| K Neighbors Regressor | 0.91 | 2022.87 | 0.03 |
| Extra Tree Regressor | 0.87 | 2406.63 | 0.02 |

**Table 4.8.** Performance attributes of the selected electricity demand model parameters under various machine learning algorithms 2

| Algorithm | R-Squared | RMSE (MW) | Training Time (s) |
|---|---|---|---|
| Gradient Boosting Regressor | 0.83 | 2722.18 | 0.26 |
| Ada Boost Regressor | 0.67 | 3799.88 | 0.24 |
| Orthogonal Matching Pursuit Cross Validation | 0.32 | 5491.85 | 0.02 |
| Least-Angle Regression | 0.32 | 5491.85 | 0.01 |
| Least-Angle Regression Cross Validation | 0.32 | 5491.85 | 0.03 |
| Lasso Least-Angle Regression Cross Validation | 0.32 | 5491.85 | 0.02 |
| Lasso Least-Angle Regression | 0.32 | 5491.85 | 0.01 |
| Linear Regression | 0.32 | 5491.85 | 0.01 |
| Transformed Target Regressor | 0.32 | 5491.85 | 0.01 |
| Ridge | 0.32 | 5491.86 | 0.01 |
| Ridge Cross Validation | 0.32 | 5491.90 | 0.01 |
| Bayesian Ridge | 0.32 | 5491.91 | 0.01 |
| Lasso | 0.32 | 5491.91 | 0.01 |
| Lasso Cross Validation | 0.32 | 5492.04 | 0.10 |
| Stochastic Gradient Descent Regressor | 0.31 | 5493.92 | 0.02 |
| Lasso Lars | 0.31 | 5498.82 | 0.01 |
| Poisson Regressor | 0.31 | 5522.72 | 0.01 |
| Huber Regressor | 0.30 | 5566.89 | 0.03 |
| Passive Aggressive Regressor | 0.29 | 5602.33 | 0.02 |
| Elastic Net | 0.28 | 5635.77 | 0.01 |
| Tweedie Regressor | 0.24 | 5804.09 | 0.01 |
| Generalized Linear Regressor | 0.24 | 5804.09 | 0.03 |
| Gamma Regressor | 0.23 | 5807.00 | 0.02 |
| Orthogonal Matching Pursuit | 0.23 | 5820.92 | 0.01 |
| Random Sample Consensus Regressor | 0.21 | 5906.53 | 0.14 |
| Elastic Net Cross Validation | 0.13 | 6192.16 | 0.10 |

**Table 4.9.** Performance attributes of the selected electricity demand model parameters under various machine learning algorithms 3

| Algorithm | R-Squared | RMSE (MW) | Training Time (s) |
|---|---|---|---|
| Support Vector Regression | 0.03 | 6531.17 | 1.61 |
| Nu Support Vector Regression | 0.02 | 6580.75 | 1.20 |
| Dummy Regressor | 0.00 | 6638.52 | 0.01 |
| Multilayer Perceptron Regressor | -13.82 | 25558.05 | 5.11 |
| Linear Support Vector Regression | -14.75 | 26343.31 | 0.01 |
| Kernel Ridge | -22.30 | 32038.79 | 2.08 |

### 4.3.2 Solar Radiance

The performance attributes of the investigated machine learning algorithms for short-term solar radiance forecasting are summarised in Tables 4.10 and 4.12 in order of ascending RMSE.

**Table 4.10.** Performance attributes of the selected PV forecasting model parameters under various machine learning algorithms 1

| Algorithm | R-Squared | RMSE ($\frac{W}{m^2}$) | Training Time (s) |
|---|---|---|---|
| Random Forest Regressor | 0.94 | 75.98 | 9.77 |
| Extra Trees Regressor | 0.94 | 76.36 | 5.86 |
| Extreme Gradient Boosting Regressor | 0.94 | 80.22 | 1.20 |
| Bagging Regressor | 0.94 | 80.61 | 1.04 |
| Light Gradient Boosted Machine Regressor | 0.94 | 80.63 | 0.47 |
| Histogram Gradient Boosting Regressor | 0.93 | 81.18 | 5.80 |
| Decision Tree Regressor | 0.89 | 105.43 | 0.17 |
| Gradient Boosting Regressor | 0.89 | 105.75 | 6.71 |
| Extra Tree Regressor | 0.87 | 112.76 | 0.10 |
| K Neighbors Regressor | 0.84 | 125.63 | 1.86 |
| Multilayer Perceptron Regressor | 0.84 | 125.92 | 17.97 |
| Ada Boost Regressor | 0.78 | 146.67 | 0.78 |

**Table 4.11.** Performance attributes of the selected PV forecasting model parameters under various machine learning algorithms 2

| Algorithm | R-Squared | RMSE ($\frac{W}{m^2}$) | Training Time (s) |
|---|---|---|---|
| Ridge | 0.63 | 192.00 | 0.02 |
| Bayesian Ridge | 0.63 | 192.00 | 0.79 |
| Transformed Target Regressor | 0.63 | 192.01 | 0.03 |
| Linear Regression | 0.63 | 192.01 | 0.79 |
| Ridge Cross Validation | 0.63 | 192.01 | 0.16 |
| Lasso Least-Angle Regression | 0.63 | 192.02 | 0.03 |
| Lasso Least-Angle Regression Cross Validation | 0.63 | 192.02 | 0.14 |
| Lasso Cross Validation | 0.63 | 192.03 | 0.39 |
| Lasso | 0.63 | 192.07 | 0.24 |
| Stochastic Gradient Descent Regressor | 0.63 | 192.08 | 0.06 |
| Least-Angle Regression | 0.63 | 193.34 | 0.28 |
| Least-Angle Regression Cross Validation | 0.62 | 193.79 | 0.13 |
| Huber Regressor | 0.62 | 194.37 | 0.25 |
| Orthogonal Matching Pursuit Cross Validation | 0.62 | 194.87 | 0.09 |
| Passive Aggressive Regressor | 0.61 | 196.53 | 0.09 |
| Linear Support Vector Regression | 0.60 | 199.14 | 0.08 |
| Elastic Net Cross Validation | 0.59 | 201.51 | 0.31 |
| Orthogonal Matching Pursuit | 0.54 | 213.45 | 0.03 |
| Elastic Net | 0.53 | 216.41 | 0.03 |
| Poisson Regressor | 0.50 | 223.90 | 0.19 |
| Nu Support Vector Regressor | 0.49 | 226.20 | 17.23 |
| Tweedie Regressor | 0.44 | 236.50 | 0.03 |
| Generalised Linear Regressor | 0.44 | 236.50 | 14.35 |
| Support Vector Regression | 0.43 | 237.96 | 17.91 |

**Table 4.12.** Performance attributes of the selected PV forecasting model parameters under various machine learning algorithms 3

| Algorithm | R-Squared | RMSE ($\frac{W}{m^2}$) | Training Time (s) |
|---|---|---|---|
| Gamma Regressor | 0.38 | 249.42 | 0.14 |
| Lasso Least-Angle Regression | 0.35 | 254.07 | 0.02 |
| Kernel Ridge | 0.20 | 282.52 | 40.49 |
| Dummy Regressor | 0.00 | 316.26 | 0.02 |
| Random Sample Consensus Regressor | -0.15 | 339.52 | 0.13 |

## 4.4 PARTICIPANT MATCHING OPTIMISATION IN ELECTRICITY MARKETS

### 4.4.1 Single Objective Optimisation

#### 4.4.1.1 Power Loss Minimisation

Optimisation of the power loss results in a total power loss of 83.6830 W when using LP. However, the total weighted transmission congestion is 81.2238 $MW^2$. The resultant power flow optimisation is presented in Table 4.13. The total transmission powers (incl. baseline congestion) are also presented in Table 4.14 to gain insight into the transmitted power in each power line. Lastly, Table 4.15 is presented to provide an overview of the summative electricity quantity schedule.

**Table 4.13.** Power flow (in W) for transmission power loss minimisation (excl. congestion)

| Participant | Producer A | Producer B | Producer C |
|---|---|---|---|
| Consumer a | 0.0042 | 2511.628 | 3488.368 |
| Consumer b | 4129.438 | 1842.583 | 2027.978 |
| Consumer c | 870.5569 | 3302.772 | 826.671 |
| Consumer d | 0.000378 | 1961.181 | 1038.819 |

**Table 4.14.** Power flow (in W) for transmission power loss minimisation (incl. congestion)

| Participant | Producer A | Producer B | Producer C |
|---|---|---|---|
| Consumer a | 0.0042 | 10511.63 | 8488.368 |
| Consumer b | 7129.438 | 7842.583 | 3027.978 |
| Consumer c | 5870.557 | 3302.772 | 7826.671 |
| Consumer d | 6000 | 3961.181 | 5038.819 |

**Table 4.15.** Electricity quantity schedule (in W)

| ID | Generation | Demand |
|---|---|---|
| A | 5000 | 6000 |
| B | 9618.164 | 8000 |
| C | 7381.836 | 5000 |
| D | - | 3000 |

#### 4.4.1.2 Transmission Congestion Minimisation

Optimisation of the transmission congestion results in total weighted transmission congestion of 19 $MW^2$ when using LP. However, the total power loss is 189.3061 W. The resultant power flow optimisation is presented in Table 4.16. The total transmission powers (incl. baseline congestion) are also presented in Table 4.17 to gain insight into the transmitted power in each power line. Lastly, Table 4.18 is presented to provide an overview of the summative electricity quantity schedule.

**Table 4.16.** Power flow (in W) for transmission congestion minimisation (excl. congestion)

| Participant | Producer A | Producer B | Producer C |
|---|---|---|---|
| Consumer a | 5000 | 0 | 1000 |
| Consumer b | 0 | 0 | 8000 |
| Consumer c | 0 | 5000 | 0 |
| Consumer d | 0 | 3000 | 0 |

**Table 4.17.** Power flow for (in W) transmission power loss minimisation (incl. congestion)

| Participant | Producer A | Producer B | Producer C |
|---|---|---|---|
| Consumer a | 5000 | 8000 | 6000 |
| Consumer b | 3000 | 6000 | 9000 |
| Consumer c | 5000 | 5000 | 7000 |
| Consumer d | 6000 | 5000 | 4000 |

**Table 4.18.** Electricity quantity schedule (in W)

| ID | Generation | Demand |
|---|---|---|
| A | 5000 | 6000 |
| B | 8000 | 8000 |
| C | 9000 | 5000 |
| D | - | 3000 |

### 4.4.2 Multi-objective Optimisation

#### 4.4.2.1 Power Loss Priority

The optimisation results in a total power loss of 83.6830 W and total weighted congestion of 50.8645 MW$^2$. The power flow schedule from the optimisation is presented in Table 4.19. The total transmission powers (incl. baseline congestion) are also presented in Table 4.20 to gain insight into the transmitted power in each power line. Table 4.21 then provides an overview of the summative electricity quantity schedule.

**Table 4.19.** Power flow (in W) for transmission loss and congestion minimisation (excl. congestion)

| Participant | Producer A | Producer B | Producer C |
|---|---|---|---|
| Consumer a | 2773.279 | 925.8326 | 2300.888 |
| Consumer b | 2226.721 | 2265.781 | 3507.498 |
| Consumer c | 0 | 4852.656 | 147.3439 |
| Consumer d | 0 | 2430.155 | 569.8448 |

**Table 4.20.** Power flow (in W) for transmission loss and congestion minimisation (incl. congestion)

| Participant | Producer A | Producer B | Producer C |
|---|---|---|---|
| Consumer a | 2773.279 | 8925.833 | 7300.888 |
| Consumer b | 5226.721 | 8265.781 | 4507.498 |
| Consumer c | 5000 | 4852.656 | 7147.344 |
| Consumer d | 6000 | 4430.155 | 4569.845 |

**Table 4.21.** Electricity quantity schedule (in W)

| ID | Generation | Demand |
|---|---|---|
| A | 5000 | 6000 |
| B | 10474.43 | 8000 |
| C | 6525.575 | 5000 |
| D | - | 3000 |

#### 4.4.2.2 Transmission Congestion Priority

The optimisation results in a total power loss of 189.3061 W and total weighted congestion of 19 MW$^2$. The power flow schedule from the optimisation is presented in Table 4.22. The total transmission powers (incl. baseline congestion) are also presented in Table 4.23 to gain insight into the transmitted power in each power line. Lastly, Table 4.24 is presented to provide an overview of the summative electricity quantity schedule.

**Table 4.22.** Power flow (in W) for transmission loss and congestion minimisation (excl. congestion)

| Participant | Producer A | Producer B | Producer C |
|---|---|---|---|
| Consumer a | 5000 | 0 | 1000 |
| Consumer b | 0 | 0 | 8000 |
| Consumer c | 0 | 5000 | 0 |
| Consumer d | 0 | 3000 | 0 |

**Table 4.23.** Power flow (in W) for transmission loss and congestion minimisation (incl. congestion)

| Participant | Producer A | Producer B | Producer C |
|---|---|---|---|
| Consumer a | 5000 | 8000 | 6000 |
| Consumer b | 3000 | 6000 | 9000 |
| Consumer c | 5000 | 5000 | 7000 |
| Consumer d | 6000 | 5000 | 4000 |

**Table 4.24.** Electricity quantity schedule (in W)

| ID | Generation | Demand |
|---|---|---|
| A | 5000 | 6000 |
| B | 8000 | 8000 |
| C | 9000 | 5000 |
| D | - | 3000 |

## 4.5 A NOVEL APPROACH TO DYNAMIC PRICING IN ELECTRICITY MARKETS

### 4.5.1 Demand Response Price Components

The demand response price components for sessions 1-3 are summarised in Tables 4.25 - 4.27, respectively.

**Table 4.25.** Demand response price components ($P_{DR}$) for session 1 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Consumer 1 | -0.7500 | -0.7357 | -0.8286 | -0.7857 |
| Consumer 2 | -0.1667 | -0.1049 | -0.1728 | -0.1420 |
| Consumer 3 | -0.6591 | -0.5909 | -0.4545 | -0.5909 |

**Table 4.26.** Demand response price components ($P_{DR}$) for session 2 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Consumer 1 | 0 | 0 | 0 | 0 |
| Consumer 2 | 0 | 0 | 0 | 0 |
| Consumer 3 | 0 | 0 | 0 | 0 |

**Table 4.27.** Demand response price components ($P_{DR}$) for session 3 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Consumer 1 | 0.2842 | 0.2895 | 0.3053 | 0.3579 |
| Consumer 2 | 0.1111 | 0.1364 | 0.0606 | 0.0960 |
| Consumer 3 | 0.1333 | 0.1333 | 0.0500 | 0.0083 |

### 4.5.2 Variable Cost Price Components

The variable cost price components for sessions 1-3 are summarised in Tables 4.28 - 4.30, respectively.

**Table 4.28.** Variable cost price components ($P_{VC}$) for session 1 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Producer A | 3.915 | 3.965 | 3.91 | 3.935 |
| Producer B | 0 | 0 | 0 | 0 |
| Producer C | 0 | 0 | 0 | 0 |

**Table 4.29.** Variable cost price components ($P_{VC}$) for session 2 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Producer A | 3 | 3 | 3 | 3 |
| Producer B | 0 | 0 | 0 | 0 |
| Producer C | 0 | 0 | 0 | 0 |

**Table 4.30.** Variable cost price ($P_{VC}$) components for session 3 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Producer A | 5.06 | 5.085 | 5.01 | 5.045 |
| Producer B | 0 | 0 | 0 | 0 |
| Producer C | 0 | 0 | 0 | 0 |

### 4.5.3 Fixed Cost Price Components

The fixed cost price components for sessions 1-3 are summarised in Tables 4.31 - 4.33, respectively.

**Table 4.31.** Fixed cost price components ($P_{FC}$) for session 1 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Producer A | 2.9363 | 2.9738 | 2.9325 | 2.9513 |
| Producer B | 2.2313 | 2.2388 | 2.1900 | 2.2125 |
| Producer C | 0 | 0 | 0 | 0 |

**Table 4.32.** Fixed cost price components ($P_{FC}$) for session 2 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Producer A | 2.25 | 2.25 | 2.25 | 2.25 |
| Producer B | 0.75 | 0.75 | 0.75 | 0.75 |
| Producer C | 0 | 0 | 0 | 0 |

**Table 4.33.** Fixed cost price components ($P_{FC}$) for session 3 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Producer A | 3.7125 | 3.7125 | 3.7125 | 3.7125 |
| Producer B | 3.5625 | 3.5625 | 3.5625 | 3.5625 |
| Producer C | 0 | 0 | 0 | 0 |

### 4.5.4 Reserve Capacity Price Components

The reserve capacity price components for sessions 1-3 are summarised in Tables 4.34 - 4.36, respectively.

**Table 4.34.** Reserve capacity price components ($P_C$) for session 1 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Consumer 1 | 0 | 0 | 0 | 0 |
| Consumer 2 | 0 | 0 | 0 | 0 |
| Consumer 3 | 0 | 0 | 0 | 0 |

**Table 4.35.** Reserve capacity cost price components ($P_C$) for session 2 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Consumer 1 | 0 | 0 | 0 | 0 |
| Consumer 2 | 0 | 0 | 0 | 0 |
| Consumer 3 | 0 | 0 | 0 | 0 |

**Table 4.36.** Reserve capacity price components ($P_C$) for session 3 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Consumer 1 | 0.297 | 0.3025 | 0.319 | 0.374 |
| Consumer 2 | 0.121 | 0.1485 | 0.066 | 0.1045 |
| Consumer 3 | 0.088 | 0.088 | 0.033 | 0.0055 |

### 4.5.5 Electricity Prices Excluding Losses and Constraints

The electricity prices before considering transmission losses and constraints for sessions 1-3 are summarised in Tables 4.37 - 4.39, respectively.

**Table 4.37.** Electricity prices ($P_E$) excluding transmission losses and constraints for session 1 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Generator A | 6.6846 | 6.8339 | 6.6697 | 6.7443 |
| Generator B | 1.481 | 1.5031 | 1.3614 | 1.4268 |
| Generator C | -0.6591 | -0.5909 | -0.4545 | -0.5909 |
| Consumer 1 | 1.481 | 1.5031 | 1.3614 | 1.4268 |
| Consumer 2 | 6.6846 | 6.8339 | 6.6697 | 6.7443 |
| Consumer 3 | -0.6591 | -0.5909 | -0.4545 | -0.5909 |

**Table 4.38.** Electricity prices ($P_E$) excluding transmission losses and constraints for session 2 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Generator A | 5.25 | 5.25 | 5.25 | 5.25 |
| Generator B | 0.75 | 0.75 | 0.75 | 0.75 |
| Generator C | 0 | 0 | 0 | 0 |
| Consumer 1 | 0.75 | 0.75 | 0.75 | 0.75 |
| Consumer 2 | 5.25 | 5.25 | 5.25 | 5.25 |
| Consumer 3 | 0 | 0 | 0 | 0 |

**Table 4.39.** Electricity prices ($P_E$) excluding transmission losses and constraints for session 3 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Generator A | 8.8836 | 8.9339 | 8.7831 | 8.8535 |
| Generator B | 3.8467 | 3.852 | 3.8678 | 3.9204 |
| Generator C | 0.1333 | 0.1333 | 0.05 | 0.0083 |
| Consumer 1 | 4.1437 | 4.1545 | 4.1868 | 4.2944 |
| Consumer 2 | 9.0046 | 9.0824 | 8.8491 | 8.958 |
| Consumer 3 | 0.2213 | 0.2213 | 0.083 | 0.0138 |

### 4.5.6 Final Electricity Prices

The final electricity prices for each participant and session are provided in Tables 4.40 - 4.42.

**Table 4.40.** Final electricity prices ($P_E$) for session 1 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Generator A | 6.6835 | 6.8328 | 6.6686 | 6.7432 |
| Generator B | 1.4806 | 1.5027 | 1.3611 | 1.4265 |
| Generator C | 0.382 | 0.388 | 0.4 | 0.388 |
| Consumer 1 | 1.4814 | 1.5035 | 1.3617 | 1.4271 |
| Consumer 2 | 6.6857 | 6.8350 | 6.6708 | 6.7454 |
| Consumer 3 | 0.382 | 0.388 | 0.4 | 0.388 |

**Table 4.41.** Final electricity prices ($P_E$) for session 2 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Generator A | 5.2494 | 5.2494 | 5.2494 | 5.2494 |
| Generator B | 0.7499 | 0.7499 | 0.7499 | 0.7499 |
| Generator C | 0.8 | 0.8 | 0.8 | 0.8 |
| Consumer 1 | 0.7501 | 0.7501 | 0.7501 | 0.7501 |
| Consumer 2 | 5.2506 | 5.2506 | 5.2506 | 5.2506 |
| Consumer 3 | 0.8 | 0.8 | 0.8 | 0.8 |

**Table 4.42.** Final electricity prices ($P_E$) for session 3 (in ZAR)

| Participant | Iteration 1 | Iteration 2 | Iteration 3 | Iteration 4 |
|---|---|---|---|---|
| Generator A | 8.8818 | 8.9320 | 8.7813 | 8.8517 |
| Generator B | 3.8451 | 3.8504 | 3.8662 | 3.9188 |
| Generator C | 0.6 | 0.6 | 0.6 | 0.6 |
| Consumer 1 | 4.1454 | 4.1562 | 4.1885 | 4.2962 |
| Consumer 2 | 9.0065 | 9.0843 | 8.8509 | 8.9598 |
| Consumer 3 | 0.688 | 0.688 | 0.633 | 0.6055 |

## 4.6 EXPLORING CONVENTIONAL SMART CONTRACT SOLUTIONS

An extract of the Ethereum smart contract user interface is provided in Fig. 4.2, with the available interaction features described by Fig. 4.3. Furthermore, the blockchain record containing the life cycle of the deployed smart contract after completing all transaction requests is presented in Fig. 4.4 and 4.5. Lastly, the final account balances for the market participants are provided in Table 4.44.

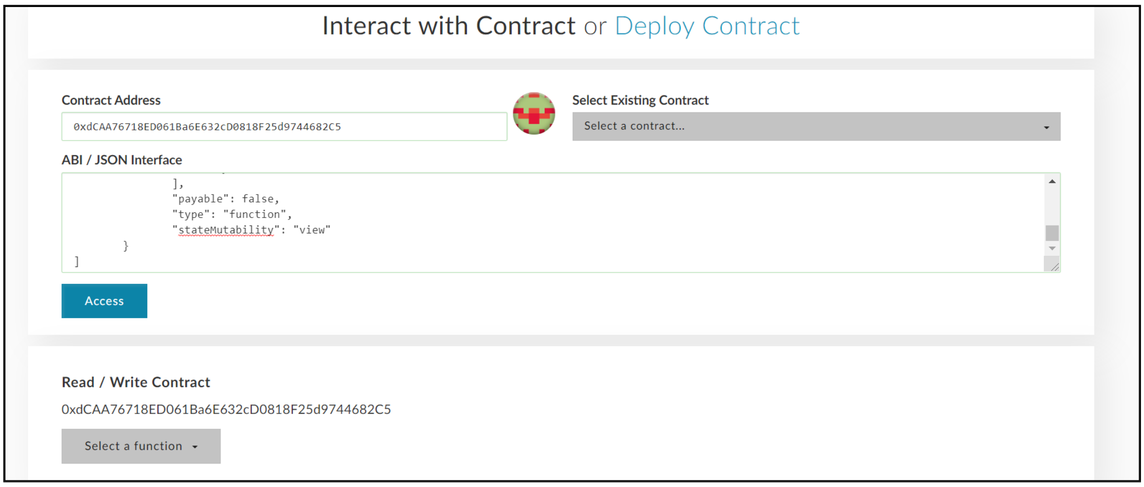



**Figure 4.2.** Smart contract user interface

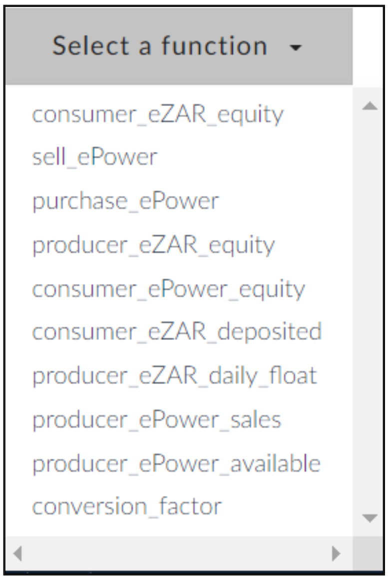



**Figure 4.3.** Available read or write functions

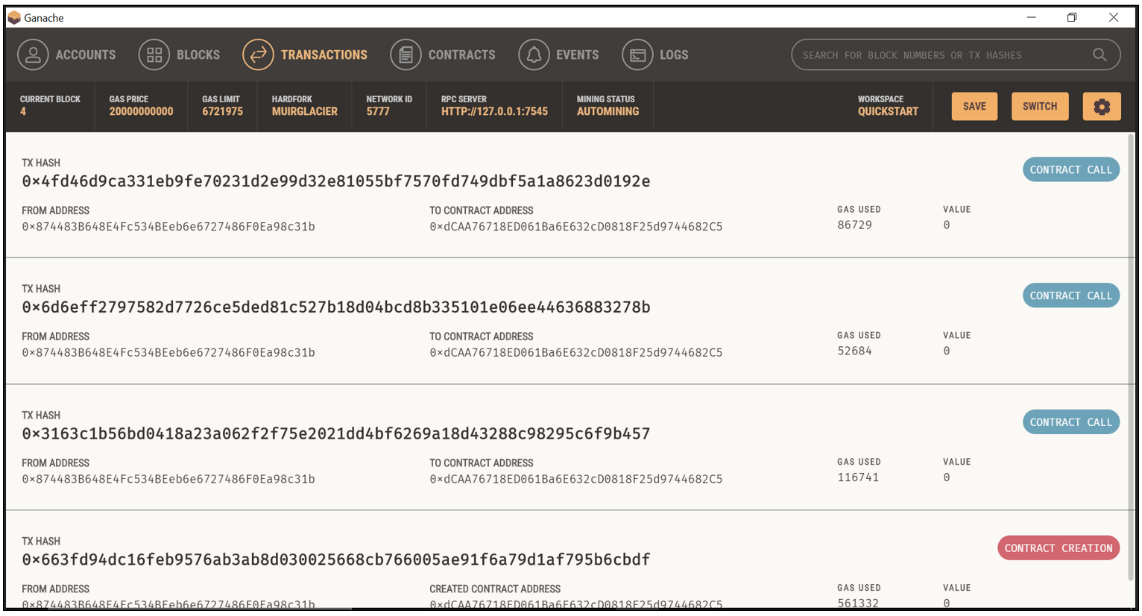



**Figure 4.4.** An overview of all the transactions registered on the Ethereum blockchain

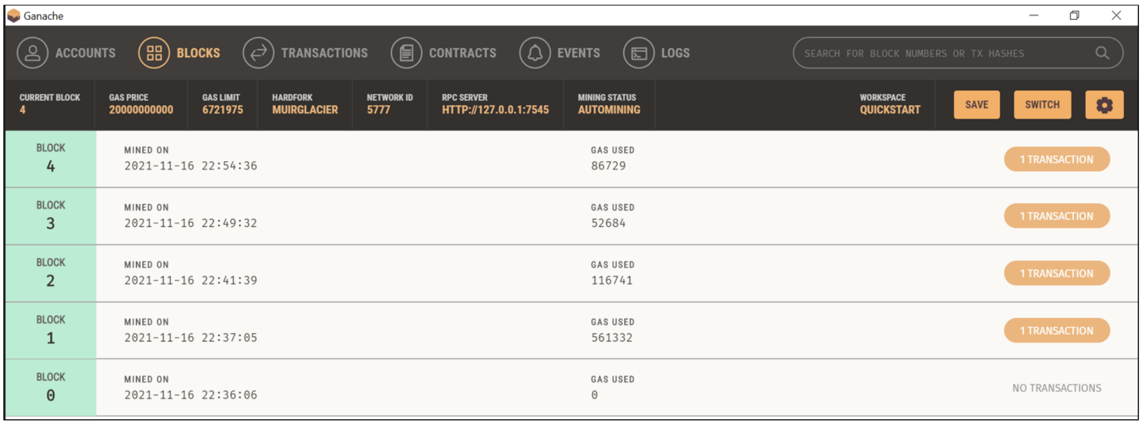



**Figure 4.5.** Blockchain containing the life cycle of the deployed smart contract on an Ethereum test network

**Table 4.43.** Reflected account balances after performing various energy exchange transactions

| Transaction | Producer | | Prosumer | | Consumer | |
|---|---|---|---|---|---|---|
| Number | eZAR | ePower | eZAR | ePower | eZAR | ePower |
| 0 | 0 | 10000 | 1000 | 0 | 1000 | 0 |
| 1 | 500 | 5000 | 500 | 5000 | 1000 | 0 |
| 2 | 350 | 6500 | 650 | 3500 | 1000 | 0 |
| 3 | 550 | 4500 | 650 | 3500 | 800 | 2000 |

## 4.7 DEVELOPMENT OF A SPECIALISED PEER-TO-PEER BLOCKCHAIN TRADING SYSTEM

An overview of the simulated energy ecosystem is described in Fig. 4.6. The complete blockchain ledger after all considered transactions is provided in Fig. 4.7 - 4.14. The extracts provide insight into the transaction details and various participant account information. Furthermore, extracts of the user interface for the market participants are included in Fig. 4.15 - 4.17. Lastly, the theoretical account values after each transaction are presented in Table 4.44 for comparison purposes.

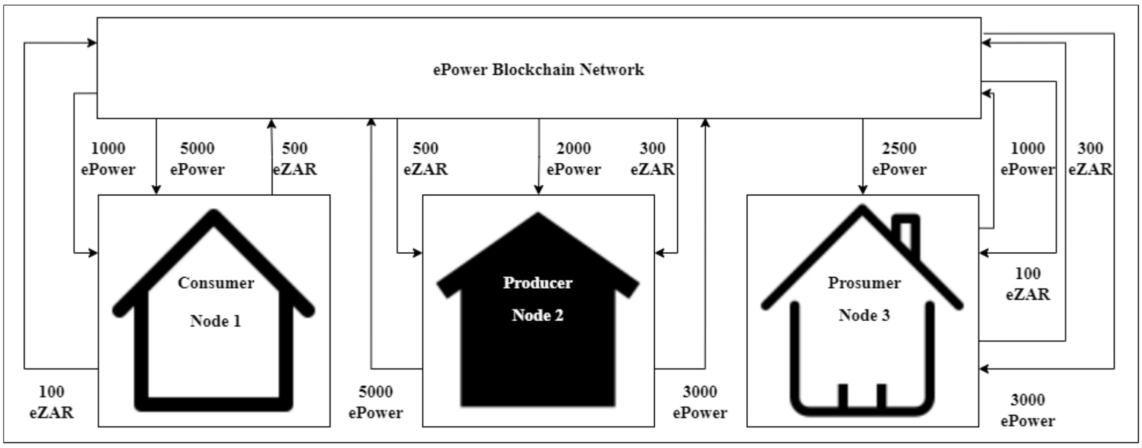



**Figure 4.6.** Simulated energy ecosystem


```
{ ⊟
   "actual_chain":[ ⊟
      { ⊟
         "index":1,
         "previous_hash":"0",
         "proof":1,
         "timestamp":"2021-12-08 14:04:29.888627",
         "transactions":[ ⊟

         ]
      },
```


**Figure 4.7.** Genesis block selected through the consensus mechanism


```
      { ⊟
         "index":2,
         "previous_hash":"0c49ba8eb596b31db153f48f21d64cc2eaf65462338acc22b4239a1f25559d51",
         "proof":533,
         "timestamp":"2021-12-08 14:09:05.294070",
         "transactions":[ ⊟
            { ⊟
               "Excessive_harmonic_distortion":0,
               "Power_quality_compliance":1,
               "Recipient":"f796220bb10848ab87e0b1cfcc4fc68c",
               "Recurring_voltage_dips":0,
               "Request_outcome":"The power quality is acceptable. ePower tokens have been issued.",
               "Updated_recipient_ePower_balance":19999.9,
               "Voltage_flicker":0
            },
            { ⊟
               "Miner_address":"miner B",
               "Miner_ePower_balance":0.1,
               "Sender_address":"f796220bb10848ab87e0b1cfcc4fc68c",
               "ePower_Gas_Reward":0.1
            }
         ]
      },
```


**Figure 4.8.** Record of transaction 1 stored on the ePower blockchain

```
{
   "index":3,
   "previous_hash":"b8094cfb640cbb01c2a7ca8c7b914dca23a3c531389e7726ea6f204d59a6b6be",
   "proof":45293,
   "timestamp":"2021-12-08 14:11:54.328590",
   "transactions":[
      {
         "Gas_in_eZAR":0.01,
         "Received_ePower_amount":"5000",
         "Receiver_address":"f0eb92c6cf084be3a2dea859551296f0",
         "Receiver_ePower_balance":5000.0,
         "Receiver_eZAR_balance":499.99,
         "Requested_ePower_amount":"5000",
         "Sender_address":"f796220bb10848ab87e0b1cfcc4fc68c",
         "Sender_ePower_balance":14999.900000000001,
         "Sender_eZAR_balance":500.0,
         "Transaction_outcome":"The transaction was successfully completed",
         "ePower_exchange_rate":10,
         "eZAR_purchase_amount":500.0
      },
      {
         "Miner_address":"miner A",
         "Miner_ePower_balance":0.1,
         "Sender_address":"f0eb92c6cf084be3a2dea859551296f0",
         "ePower_Gas_Reward":0.1
      }
   ]
},
```


**Figure 4.9.** Record of transaction 2 stored on the ePower blockchain


```
{
   "index":4,
   "previous_hash":"67022d83720d72b316e51478f66668ec4f5eff460c4f72bc128797f68e49efcb",
   "proof":21391,
   "timestamp":"2021-12-08 14:14:29.792312",
   "transactions":[
      {
         "Excessive_harmonic_distortion":0,
         "Power_quality_compliance":1,
         "Recipient":"66a19586dda24c9484eb0a36abf4e02d",
         "Recurring_voltage_dips":0,
         "Request_Outcome":"The power quality is acceptable. ePower tokens have been issued.",
         "Updated_recipient_ePower_balance":2499.9,
         "Voltage_flicker":0
      },
      {
         "Miner_address":"miner C",
         "Miner_ePower_balance":0.1,
         "Sender_address":"66a19586dda24c9484eb0a36abf4e02d",
         "ePower_Gas_Reward":0.1
      }
   ]
},
```


**Figure 4.10.** Record of transaction 3 stored on the ePower blockchain

```
{
  "index":5,
  "previous_hash":"f52759dc62ed3d87b8952295a5bb0c020cb1c8e145da70860f3a7ba408becca3",
  "proof":8018,
  "timestamp":"2021-12-08 14:17:01.297121",
  "transactions":[
    {
      "Gas_in_eZAR":0.01,
      "Received_ePower_amount":"3000",
      "Receiver_address":"66a19586dda24c9484eb0a36abf4e02d",
      "Receiver_ePower_balance":5499.9,
      "Receiver_eZAR_balance":1199.99,
      "Requested_ePower_amount":"3000",
      "Sender_address":"f796220bb10848ab87e0b1cfcc4fc68c",
      "Sender_ePower_balance":11999.900000000001,
      "Sender_eZAR_balance":800.0,
      "Transaction_outcome":"The transaction was successfully completed",
      "ePower_exchange_rate":10,
      "eZAR_purchase_amount":300.0
    },
    {
      "Miner_address":"miner C",
      "Miner_ePower_balance":0.2,
      "Sender_address":"66a19586dda24c9484eb0a36abf4e02d",
      "ePower_Gas_Reward":0.1
    }
  ]
},
```


**Figure 4.11.** Record of transaction 4 stored on the ePower blockchain


```
{
  "index":6,
  "previous_hash":"e65a8f6f2b471e442767d3342d3a01a4d457552f147e6aac01522dd22cda86c2",
  "proof":48191,
  "timestamp":"2021-12-08 14:20:44.531161",
  "transactions":[
    {
      "Gas_in_eZAR":0.01,
      "Received_ePower_amount":"1000",
      "Receiver_address":"f0eb92c6cf084be3a2dea859551296f0",
      "Receiver_ePower_balance":6000.0,
      "Receiver_eZAR_balance":399.98,
      "Requested_ePower_amount":"1000",
      "Sender_address":"66a19586dda24c9484eb0a36abf4e02d",
      "Sender_ePower_balance":4499.9,
      "Sender_eZAR_balance":1299.99,
      "Transaction_outcome":"The transaction was successfully completed",
      "ePower_exchange_rate":10,
      "eZAR_purchase_amount":100.0
    },
    {
      "Miner_address":"miner A",
      "Miner_ePower_balance":0.2,
      "Sender_address":"f0eb92c6cf084be3a2dea859551296f0",
      "ePower_Gas_Reward":0.1
    }
  ]
},
```


**Figure 4.12.** Record of transaction 5 stored on the ePower blockchain

```
      {
         "index":7,
         "previous_hash":"cc8c3df60268f1a4a54ce658028f40546f5c7f0f9449f1ed4d80a20cb214501b",
         "proof":19865,
         "timestamp":"2021-12-08 14:22:56.577053",
         "transactions":[
            {
               "Recipient":"f796220bb10848ab87e0b1cfcc4fc68c",
               "Recipient_ePower_balance":11999.900000000001,
               "Request_outcome":"The power quality is unacceptable. ePower tokens have NOT been issued.",
               "excessive_harmonic_distortion":1,
               "power_quality_compliance":0,
               "recurring_voltage_dips":0,
               "voltage_flicker":0
            },
            {
               "Miner_address":"miner B",
               "Miner_ePower_balance":0.2,
               "Sender_address":"f796220bb10848ab87e0b1cfcc4fc68c",
               "ePower_Gas_Reward":0.1
            }
         ]
      },
```


**Figure 4.13.** Record of transaction 6 stored on the ePower blockchain


```
      {
         "index":8,
         "previous_hash":"fddc83436f7324116a2d2a24d7198faafa8eff4ff2969b9fd4a017e7fb3ac9c5",
         "proof":95063,
         "timestamp":"2021-12-08 14:26:07.774039",
         "transactions":[
            {
               "Gas_in_eZAR":0.01,
               "Received_ePower_amount":11999.900000000001,
               "Receiver_address":"66a19586dda24c9484eb0a36abf4e02d",
               "Receiver_ePower_balance":16499.800000000003,
               "Receiver_eZAR_balance":99.98999999999977,
               "Requested_ePower_amount":"12500",
               "Sender_address":"f796220bb10848ab87e0b1cfcc4fc68c",
               "Sender_ePower_balance":0.0,
               "Sender_eZAR_balance":1999.9900000000002,
               "Transaction_outcome":"The transaction was partially completed due to insufficient ePower available",
               "ePower_exchange_rate":10,
               "eZAR_purchase_amount":1199.9900000000002
            },
            {
               "Miner_address":"miner C",
               "Miner_ePower_balance":0.30000000000000004,
               "Sender_address":"66a19586dda24c9484eb0a36abf4e02d",
               "ePower_Gas_Reward":0.1
            }
         ]
      }
   ],
   "message":"The chain was not replaced as this is the largest one."
}
```


**Figure 4.14.** Record of transaction 7 stored on the ePower blockchain

```
{
    "1eZAR_equivalent": "10 ePower",
    "Conversion_rate": 10,
    "Producer_ePower_balance": 0.0,
    "Prosumer_ePower_balance": 16499.800000000003,
    "Transaction_gas_fee": "0.1 ePower",
    "Transaction_gas_fee_equivalent": "0.01 eZAR",
    "Your_ePower_balance": 6000.0,
    "Your_eZAR_balance": 399.98,
    "Your_wallet_address": "f0eb92c6cf084be3a2dea859551296f0"
}
```


**Figure 4.15.** Energy exchange information accessed from the energy consumer's perspective


```
{
    "1eZAR_equivalent": "10 ePower",
    "Consumer_ePower_balance": 6000.0,
    "Conversion_rate": 10,
    "Producer_ePower_balance": 0.0,
    "Prosumer_ePower_balance": 16499.800000000003,
    "Transaction_gas_fee": "0.1 ePower",
    "Transaction_gas_fee_equivalent": "0.01 eZAR",
    "Your_eZAR_balance": 1999.9900000000002,
    "Your_wallet_address": "f796220bb10848ab87e0b1cfcc4fc68c"
}
```


**Figure 4.16.** Energy exchange information accessed from the energy producer's perspective


```
{
    "1eZAR_equivalent": "10 ePower",
    "Consumer_ePower_balance": 6000.0,
    "Conversion_rate": 10,
    "Producer_ePower_balance": 0.0,
    "Transaction_gas_fee": "0.1 ePower",
    "Transaction_gas_fee_equivalent": "0.01 eZAR",
    "Your_ePower_balance": 16499.800000000003,
    "Your_eZAR_balance": 99.98999999999977,
    "Your_wallet_address": "66a19586dda24c9484eb0a36abf4e02d"
}
```


**Figure 4.17.** Energy exchange information accessed from the energy prosumer's perspective

**Table 4.44.** Predicted energy exchange balances among various energy ecosystem stakeholders

| Transaction Number | Consumer | | Producer | | Prosumer | |
|---|---|---|---|---|---|---|
| | eZAR | ePower | eZAR | ePower | eZAR | ePower |
| 0 | 1000 | 0 | 0 | 0 | 1500 | 0 |
| 1 | 1000 | 0 | 0 | 20000 | 1500 | 0 |
| 2 | 500 | 5000 | 500 | 15000 | 1500 | 0 |
| 3 | 500 | 5000 | 500 | 15000 | 1500 | 2500 |
| 4 | 500 | 5000 | 800 | 12000 | 1200 | 5500 |
| 5 | 400 | 6000 | 800 | 12000 | 1300 | 4500 |
| 6 | 400 | 6000 | 800 | 12000 | 1300 | 4500 |
| 7 | 400 | 6000 | 2000 | 0 | 100 | 16500 |

**Table 4.45.** Summary of final account balances of each market participant

| Consumer | | Producer | | Prosumer | |
|---|---|---|---|---|---|
| eZAR | ePower | eZAR | ePower | eZAR | ePower |
| 399.98 | 6000 | 1999.99 | 0 | 99.99 | 16499.80 |

**Table 4.46.** Summary of final account balances of each network miner

| Miner A | | Miner B | | Miner C | |
|---|---|---|---|---|---|
| eZAR | ePower | eZAR | ePower | eZAR | ePower |
| 0 | 0.2 | 0 | 0.2 | 0 | 0.3 |

# CHAPTER 5 DISCUSSION OF THE INVESTIGATED ELECTRICITY MARKET SYSTEM

## 5.1 CHAPTER OVERVIEW

This chapter provides a critical analysis and discussion of research findings from experimentation. It further interprets the outcomes of analysis tools such as validity and reliability tests. Lastly, it accounts for possible study limitations, areas of improvement and research opportunities. An overview of each section is provided as follows.

### 5.1.1 Investigating Traditional Electricity Market Approaches

Section 5.2 evaluates the feasibility of traditional single-sided and double-sided electricity markets by considering factors such as efficiency, accuracy, participant matching and market power of the approaches. The final electricity prices for each market are also critically assessed through market clearing price comparisons of participants' average and weighted average prices. The findings of the overall analysis are then used to identify areas for future improvement.

### 5.1.2 Comparison of Popular Machine Learning Techniques for Short-Term Energy Forecasting

Section 5.3 collectively reviews the performance results of trained models for short-term energy forecasting applications. It begins by highlighting favourable baseline selection criteria for the performance measures. The trained models are then independently evaluated for the feasibility of electricity demand and solar radiation forecasting. The performance measures selected for evaluation are $R^2$, RMSE and the time taken to train the model. Trade-offs among these measures are equally considered. Each evaluation begins with the identification of spurious values. The top-performing models are then identified and contrasted with the mean and other models. Lastly, study limitations are considered and research opportunities are provided.

### 5.1.3 Participant Matching Optimisation in Electricity Markets

Section 5.4 systematically analyses various optimisation strategies for participant matching in electricity markets. It begins by identifying the best possible optimisation outcomes, which serve as baseline performance references throughout the evaluation. After that, the single-objective problems are analysed by comparing outcomes in terms of deviations from the minimal possible power loss and congestion totals. The optimisation results of the multi-objective problem are then compared with the results from the single-objective optimisations whilst noting improvements. Lastly, the limitations of the study and research opportunities are discussed.

### 5.1.4 A Novel Approach to Dynamic Pricing in Electricity Markets

Section 5.5 evaluates the proposed dynamic pricing strategy against several design goals to promote fair and equitable pricing in electricity markets. This process entails discussing how each goal is satisfied and providing substantiation of the approach by analysing the results from the simulated case study. The analysis considers real-time pricing, microgrid energy conditions, price volatility, market power, demand response, renewable energy incentivisation, and generation capacity investment. Lastly, study limitations are considered and research opportunities are provided.

### 5.1.5 Exploring Conventional Ethereum Smart Contract Solutions

Section 5.6 evaluates the developed Ethereum smart contract solution by considering various factors such as functionality, decentralisation, transparency and scalability. Design limitations in the smart contract are then highlighted. Lastly, the study's limitations are discussed before providing promising research opportunities.

### 5.1.6 Development of a Specialised Peer-to-Peer Blockchain Trading System

Section 5.7 thoroughly evaluates the developed peer-to-peer blockchain trading system. It begins by analysing the system and its characteristics. The system is then evaluated for compliance with fundamental blockchain design principles identified in the literature. After that, the transaction results are then interpreted and assessed against the designed smart contract requirements. Lastly, an extensive discussion of the study's limitations and research opportunities is provided.

## 5.2 INVESTIGATING TRADITIONAL ELECTRICITY MARKET APPROACHES

### 5.2.1 Single-sided Electricity Markets

A uniform price strategy is investigated in this case study with the price of electricity corresponding to 32 $\frac{\text{ZAR}}{\text{kWh}}$ for all successful electricity exchanges. This market clearing price is 21.67% and 31.65%

higher than the average and weighted average prices, respectively. However, the price selection approach accurately represents electricity market value by accounting for the sale volumes.

The pricing strategy considers the collective electricity demand in price determination. As a result, only 58.29% of electricity is sold, with the remaining offers rejected. Consequently, the market demonstrates the ability to account for supply and demand when determining participant matching.

Furthermore, the uniform price approach in this market favours lower prices by prioritising the energy on sale from the lowest sale amount until the demand is met. This simplistic approach promotes market competitiveness among electricity producers whilst offering ease of implementation. It also incentivises producers to reduce marginal costs and markups to prevent conditions of unsold electricity capacity. In addition, uniform prices among all participants mitigate price discrimination.

Despite the advantages of this market approach, there are two key disadvantages. Firstly, uniform prices are rigid, which can disadvantage consumers. This limitation is evident when considering the case study. Producer B initially offered electricity at an exchange rate of 10 $\frac{\text{ZAR}}{\text{kWh}}$, which is 68.75% lower than the determined uniform market price. Therefore, producers benefit from the configuration. In contrast, consumers do not, as they may be charged as much as 220% more than the initial electricity offer price. Secondly, the strategy does not effectively manage market power when considering lower market liquidity conditions. For example, electricity producers may collaborate to increase electricity prices. As a result, the market will be cleared at higher prices without considering the impact on electricity consumers.

### 5.2.2 Double-sided Electricity Markets

#### 5.2.2.1 Market Clearing Pricing and Scheduling Optimisation

The optimisation results in a uniform market clearing price (MCP) of 30 $\frac{\text{ZAR}}{\text{kWh}}$, which is 17.65% and 12.03% higher than the average and weighted average producer offer prices, respectively. Higher price deviations exist between the MCP and average consumer bid prices, with the MCP being 50% and 31.94% higher than the average and weighted average consumer prices, respectively.

Equilibrium energy balance conditions are strictly considered as the MCP corresponds to the intersection of the supply and demand curves. Consequently, the area between the signed curves, representing social welfare, is maximised. Furthermore, the spread between the MCP and average participant price is attributed to the energy scheduling approach in the optimisation. It performs order matching by prioritising lower offer prices from producers and higher bid prices from consumers. Therefore, the approach counters the price disparity in submitted offers and bids between both classes of participants. However, there are no mitigation measures against the risks of market power abuse. This approach also does not incentivise demand response as electricity prices are uniform.

#### 5.2.2.2 Auction-based Market Clearing

Auction-based operation maximises the value of exchange whilst serving as a neutral and inexpensive platform for market liquidity. Electricity exchanges are settled at varying prices depending on the submitted market orders and bids, which introduce a degree of dynamic pricing to electricity. As a result, it provides an opportunity for increased demand response. These are all favourable characteristics for continuous and short-term trading scenarios. In cases with competing offer prices between participants, orders are filled through the *Fist-In-First-Out* principle. The application of this principle is evident when considering Producers F and G and Consumers A, B and D in the case study.

The approach may fail to cater to the entire market demand, such as in the case of Consumer G. Consumer G's order request was unfilled as the submitted bid was less than the lowest producer's offer. As a result, only 91.58% of the electricity demand was met. The extent of unmatched orders may further be emphasised in low liquidity markets. Consequently, order matching through pricing is not optimal when considering meeting the entire demand. Furthermore, the simulation demonstrates a clear emphasis on the vulnerability of the approach to market power. The market configuration is structured with the market power in favour of the electricity producers, with consumer bids greater than or equal to producer offers being cleared. Consequently, consumer prices converge toward prices dictated by generators.

### 5.2.3 Study Limitations and Research Opportunities

The findings of this investigation are limited to the considered case studies. The study can be improved by considering multiple market sessions and more practical implementation scenarios. Further research is required, focusing on improving pricing and participant matching strategies to address the shortcomings of current electricity market approaches.

## 5.3 COMPARISON OF POPULAR MACHINE LEARNING TECHNIQUES FOR SHORT-TERM ENERGY FORECASTING

### 5.3.1 Baseline Selection Criteria

#### 5.3.1.1 R-score Selection Criteria

The regression score (R-score) measures the variance of the data explained by the trained models, i.e. the model fit accuracy. Typical R-score ranges are between 0 and 1, with 1 being the most favourable regression performance.

#### 5.3.1.2 RMSE Selection Criteria

Root mean square error (RMSE) provides insight into the extent of systematic errors within the machine learning model predictions and is characterised by its ease of interpretation. This indicator additionally offers the advantage of being robust to outliers. An RMSE closer to zero is favoured when evaluating the trained models.

#### 5.3.1.3 Time Taken Selection Criteria

The time taken to train the models serves as a measure of the computational requirements of the algorithm. It is factored in as the machine learning models must adapt due to the non-stationarity of the forecast parameters. The non-stationarity is attributed to climate change and the behavioural shifts of end users. Dynamic model retraining is, therefore, necessary to mitigate covariate shift and concept drift. For these robust applications, shorter model training times are favourable.

#### 5.3.1.4 Overall Selection Criteria

A common trade-off exists in machine learning known as the *bias-variance-complexity*. Higher R-score values correspond to lower RMSE values and vice versa demonstrating inverse proportionality. Furthermore, algorithms requiring shorter model training times sustain poorer performances in R-score and RMSE, demonstrating inverse proportionality. Selections are performed by selecting models among the best performances in R-score, RMSE and training times. The final selection considers the most optimal balance among these three criteria.

### 5.3.2 Electricity Demand Forecasting

Spurious performance results are first identified as they influence the reliability and accuracy of the overall model analysis. The Kernel Ridge, Linear Support Vector Regression and Multi-layer Perceptron Regressor models exhibit negative R-scores, rendering them unsuitable for electricity demand forecasting. Therefore, these models are disregarded in the analysis. The average performances of the remaining models for R-score, RMSE and training time are 0.4595, 4506.8764 MW and 0.3021 s, respectively.

The Extreme Gradient Boosting (XGB) Regressor is the best-performing model out of the 42 investigated. It exhibits the highest R-score and lowest RMSE, corresponding to 0.98 and 833.32 MW, respectively. The model is well-fitted with a 2% deviation from the ideal scenario for R-score performance and offers an 81.51% lower RMSE than the mean. However, it does not have the fastest training time with a measured amount of 0.23 s. This training period is still favourable as it is 23.87% less than the mean, which indicates robustness. The superiority of the XGB Regressor is seen when comparing it to the second-best performing model - the Random Forest Regressor (RFR). The RFR exhibits similar R-score performances to the XGB Regressor, with its R-score being 1% lower. However, it lacks in performance when considering the RMSE and training time. The RFR model has a 41.56% higher RMSE than the XGB Regressor. Furthermore, it has a 224.4% longer training time than the mean of all the considered models.

### 5.3.3 Solar Radiation Forecasting

The Random Sampling Consensus Regressor model exhibits an impractical R-score. Consequently, it is disregarded from the analysis as it results in an unstable model unsuitable for solar radiation forecasting. The average performances of the remaining models for R-score, RMSE and training time are 0.64, 179.6035 $\frac{\mathrm{W}}{\mathrm{m}^2}$ and 3.65125 s, respectively.

Five top-performing machine learning models are identifiable, with identical R-score performances and marginal RMSE differences. However, there are significant deviations in model training times. The RFR results in a model with the highest R-score (0.94) and lowest RMSE (75.98 $\frac{\mathrm{W}}{\mathrm{m}^2}$). Despite these exceptional performance measures, it has a 167.58% longer training time than the mean. Therefore, this model is infeasible. The Extra Trees Regressor (ETR) is the next best performer for RMSE with an error estimate 0.5% larger than the RFR, making it a close competitor. The ETR demonstrates its superiority when considering its 40.02% shorter training time than the RFR. However, this model's training duration is still 60.49% above the mean. Consequently, the XGB Regressor is considered. This model exhibits the same R-score as the RFR but differs in terms of RMSE and training times. The XGB Regressor has a 5.58% higher RMSE than the RFR but is still 55.33% more accurate than the mean. Furthermore, it can significantly out-compete the RFR and ETR in training times by 87.72% and 79.52%, respectively. The XGB Regressor algorithm also demonstrates robustness compared to the other models, with a 67.13% faster training time than the mean.

### 5.3.4 Study Limitations and Research Opportunities

The limiting factors in this research are the quality of data, selection of features, validation measures and algorithm parameters. Consequently, it is recommended that various data sets and features be investigated to mitigate the risks of sample bias. In addition, evaluating the performance of the models with real-time data will more significantly enhance the integrity of the research. The reliability of the findings can further be improved by incorporating additional validation measures such as k-fold cross-validation. Furthermore, generic hyper-parameters were employed in the investigated machine learning models. Therefore, there is an opportunity to improve these model performances through hyper-parameter optimisation tuning. Lastly, the study only considers machine learning models, but there are also promising applications for deep learning techniques. Further research comparing deep learning algorithms with the currently investigated machine learning models is recommended.

## 5.4 PARTICIPANT MATCHING OPTIMISATION IN ELECTRICITY MARKETS

### 5.4.1 Summary of Optimisation Best Performances/baselines

The lowest transmission power loss total corresponds to 83.6830 W from the single objective and multi-objective power loss priority optimisations. At the same time, the lowest weighted congestion total corresponds to 19 $MW^2$ from the single objective and multi-objective congestion priority optimisations. Furthermore, the optimisations could all comply with the identified constraints, such as meeting the total demand and not exceeding generational and transmission capacities.

### 5.4.2 Single Objective Optimisations Analysis

Single objective optimisations produce favourable outcomes when considering individual parameters. However, trade-offs occur between the total transmission loss and congestion for different participant matching and power flow configurations. In the case of power loss optimisation, there is a total weighted congestion increase of 427.49% compared to the minimal possible congestion level. Similarly, the congestion optimisation results in an increased power loss total of 226.22% compared to the lowest possible loss amount. Therefore, transmission power loss and congestion minimisation are competing objectives.

### 5.4.3 Multi-Objective Optimisation

Preemptive multi-objective optimisations enable the placing of a priority objective to avoid jeopardising the primary goal of the optimisation. Prioritisation of transmission loss minimisation results in more feasible coordination of participants and power flow. The optimisation results in minimal total power loss, with significantly improved total weighted congestion levels compared to the single objective by 37.38%. In contrast, the power loss could not be further minimised when prioritising transmission congestion. As a result, the optimisation solution is the same as that of the single-objective congestion optimisation. This observation indicates the lack of flexibility in the optimisation approach compared to power loss prioritisation.

### 5.4.4 Study Limitations and Research Opportunities

The study's findings are limited to the considered case study and optimisation-solving approaches. The reliability of the results from the suggested optimisation approaches can be improved by investigating a more diverse range of practical case study scenarios. Such case studies include excess electricity demand conditions, multiple sessions and larger market data sets. Furthermore, the accuracy of the results can be improved by investigating different optimisation algorithms and solvers. For instance, preemptive multi-objective optimisation has been performed, which does not prioritise both objective functions equally. Non-preemptive multi-objective optimisation is recommended for further investigation, provided a trade-off between transmission loss and congestion is acceptable.

## 5.5 A NOVEL APPROACH TO DYNAMIC PRICING IN ELECTRICITY MARKETS

### 5.5.1 Real-time Pricing

The strategy achieves real-time pricing by factoring in real-time electricity demand and generation in the price formulation. In the case study, electricity demand samples are taken every 15 minutes. These samples are then used to generate new price iterations dynamically according to the energy supply and demand conditions. As a result, four price iterations are made for every one-hour-ahead energy forecast. The price iterations can be increased per the system requirements to capture more minor variations in the microgrid's energy conditions, provided the computational requirements are met.

### 5.5.2 Microgrid Energy Conditions

The proposed pricing strategy thoroughly considers microgrid energy conditions through $P_{DR}$. The component incorporates a base rate and ratio. The base rate is determined according to the forecasted energy balance conditions and is used to manage the degree of demand response needed. The ratio further accounts for real-time electricity demand and generation between paired participants. In the case study, the base rates are determined according to the extent of the overall microgrid electricity surplus or deficit conditions. An 8.33% electricity surplus is evident when utilising the forecasts for session 1. Therefore, a corresponding base rate of 5 $\frac{\text{ZAR}}{\text{W}}$ is selected. Session 2 forecasts corresponded to equilibrium conditions resulting in a base rate of 0. Session 3 forecasts corresponded to a 2.31% electricity deficit. As a result, a base rate of 2.5 $\frac{\text{ZAR}}{\text{W}}$ is enforced. The ratio then accounts for real-time electricity supply and demand to select the price propagation direction and scale the demand response incentive accordingly.

### 5.5.3 Price Volatility

Various aspects of the price strategy mitigate price volatility. Firstly, the price steps for each iteration are limited to scaled ratios of base rates, such as in the case of the demand response component. Secondly, a diverse range of variables is considered in the final electricity prices, which depend on external factors such as energy conditions and fixed costs of production. As a result, participant bid inputs are unrequired. This characteristic makes electricity prices more resilient to price volatility. Lastly, the final electricity prices are constrained to boundaries such as the maximum market price for electricity and the minimum rate of return. These boundaries serve to limit electricity prices to a justifiable range. The mitigation of price volatility is evident in the simulated case study. When considering Consumer 1 in session 3, electricity average price deviations are observed to be within 0.26% - 2.57% per iteration.

### 5.5.4 Market Power

The price strategy is developed to autonomously determine electricity prices by considering external and practical factors. At the same time, prices are determined at increased granularity with specialised prices for each participant. These approaches limit the influence of market participants on electricity prices. Specialised price components are also considered in the dynamic pricing scheme to distribute cost factors. As a result, market power by electricity generators cannot be exploited. For instance, variable costs are driven by the market price of fuel and the fuel consumption rates in a generation. Therefore, the price contribution cannot be increased without justifiable means. Furthermore, the costs of transmission losses are evenly distributed among both participant categories. This approach promotes fairer market conditions compared to conventional schemes. These characteristics are confirmed through the considered case study.

### 5.5.5 Demand Response

A specialised price component ($P_{DR}$) is responsible for ensuring demand response and adaptive pricing. The component consists of a base demand response coefficient and a scaling factor. The coefficient influences the demand response's aggressiveness required to ensure supply and demand conditions are met. The scaling factor accounts for real-time energy conditions between matched participants. In cases of electricity surplus, the scaling factor is negative. As a result, $P_{DR}$ is negative and reduces the overall electricity price. Whereas in cases of electricity deficit, the scaling factor is positive. Consequently, $P_{DR}$ is positive and contributes to a price increase. The scaling factor also employs the ratio between the difference of supply and demand to the supply contributing to added control of the extent of demand response incentive. In scenarios with significant imbalance, the price impact of $P_{DR}$ is significantly increased. In scenarios with ideal supply and demand balance, the $P_{DR}$ price impact is zero/negligible.

The influence of this design feature is evident in the case study. Session 1 represents excess energy conditions resulting in an average $P_{DR}$ of -0.775 ZAR for Consumer 1, -0.1446 ZAR for Consumer 2 and -0.5739 ZAR for Consumer 3. Whereas session 2 represents energy balance conditions resulting in $P_{DR}$ being zero for all participants. Lastly, session 3 represents energy excess conditions. In these circumstances, the price strategy resulted in an average $P_{DR}$ of 0.3092 ZAR for Consumer 1, 0.1010 ZAR for Consumer 2 and 0.0813 ZAR for Consumer 3.

Furthermore, the price strategy accounts for consumer capacity costs ($P_C$). This price subcomponent serves as a further incentive for demand response as the overall electricity prices increase when there are deficits in electricity balance conditions. This price component accounts for 7.69% of the overall electricity price when considering the mean prices in session 3 for Consumer 1.

### 5.5.6 Renewable Energy Usage Incentivisation

The usage of renewable energy is incentivised by offering lower electricity prices compared to conventional power generation methods. This characteristic is achieved by accounting for variable and fixed production costs individually. Variable production costs typically correspond to fuel costs and frequently contribute to the bulk of electricity costs. Renewable generators generally do not consider variable costs, and a similar relationship exists with fixed costs. As a result of these costs of production components, renewable energy is significantly cheaper than conventional electricity generation, which incentivises renewable power usage. These price characteristics are evident in the case study, with Generator C offering the lowest electricity prices. Generator A operates a diesel generator with variable costs accounting for 57.10% of its overall average electricity price. In contrast to Generator C, its average final electricity prices are 91.47% more.

### 5.5.7 Generation Capacity Investment

Ensuring generation capacity is promoted through the pricing strategy in two ways. Firstly, a minimum price constraint is enforced to ensure electricity generators do not receive inadequate compensation.

The price constraint is determined according to a competitive minimum rate of return. As a result, electricity generators can receive a steady investment return for each electricity sale. This attribute further incentivises consumers to invest in renewable systems as it will enable an extra source of income for excess renewable electricity whilst minimising electricity costs. The effects of this minimum price constraint are evident in the case study when considering the electricity prices for Consumer 3 and Generator A for all the market sessions. Secondly, the strategy increases price space granularity through specialised prices for each market participant. Consequently, investors may identify specific areas in the power system that lack generation capacity for investment opportunities.

### 5.5.8 Study Limitations and Research Opportunities

There is an intrinsic need for advanced monitoring, computational and communication infrastructure to provide accurate insight into microgrid operations. The data considered in this investigation enables insight into the inner workings of the proposed strategy. However, the performance evaluation of the pricing scheme is limited to the simulated case study. The data quality influences the price strategy's reliability and the degree of price iterations. As a result, it is recommended that the system be investigated in a practical configuration using real-time data monitoring, forecasting and processing to capture the approach's performance accurately. Furthermore, the extent of demand response of the pricing strategy is limited to the flexibility of end users, which is not always possible. Research into future demand response policies, such as smart automation technology and building energy management systems, is recommended to increase electricity consumer price sensitivity.

## 5.6 EXPLORING CONVENTIONAL ETHEREUM SMART CONTRACT SOLUTIONS

### 5.6.1 Smart Contract Design

The smart contract developed and deployed on a virtual Ethereum network addresses the requirements of trust, computational logic and automatic execution of digital energy exchanges. Trust among ecosystem participants is promoted by deploying the transactions and smart contracts on an established blockchain network containing many validators. Furthermore, the status of appropriate variables (e.g. eZAR and ePower balances) are publicly accessible along with the contract, demonstrating the system's transparency of the energy exchanges. Users can also dynamically interact with the smart contract through read and write commands without disclosing personal information. Lastly, computational logic has been employed to enforce the terms of various energy exchanges in an automated and predictable manner. An example is incorporating the modifier function to ensure that only valid transactions can be processed.

### 5.6.2 System Functionality

The system functions as anticipated. Different energy users could initiate exchanges such as the sale and resale of ePower tokens through written commands to the smart contract. The equity of all involved parties could then be retrieved from the smart contract through reading commands. The values retrieved corresponded to the theoretical amounts projected in Table 4.44 for all transactions performed (transactions 1-3). Evidently, the smart contract functions as expected, with the terms of the traditional contract automatically executed under various scenarios. In addition, users have been represented as nodes on the Ethereum network, characterised by private and public key addresses. This characteristic enhances the system's integrity by eliminating the risk of bias and privacy infringement.

### 5.6.3 Design Limitations

The study performed investigated the functionality of Ethereum-based smart contracts for three classes of energy ecosystem stakeholders. The findings are, however, limited to a centralised energy provider configuration. The system proposed can accommodate decentralised energy production by deploying numerous smart contracts on the blockchain. It is envisioned that each energy producer will independently deploy a smart contract to manage their exchanges, whilst energy consumers can interact with numerous smart contracts. Another significant limitation is that inputs to the smart contract have either been initialised at the contract deployment stage or manually supplied through myetherwallet when users initiated transactions. This limitation can be overcome with greater infrastructure, such as sensor inputs and decentralised applications, for enhanced user experience.

### 5.6.4 Study Limitations and Research Opportunities

Ethereum has been developed to cater for the general smart contract market. Despite being well established, the blockchain network suffers from a fundamental limitation - scalability. With the growing demand for smart contracts and decentralised applications, a more significant strain is being placed on the system, resulting in increased transaction fees (gas costs). Operating on the infrastructure is, therefore, unsustainable. As a result, it is recommended that a custom blockchain network be created to achieve a more optimal balance between areas such as scalability, security, complexity and performance (speed). In addition, incorporating a decentralised application is suggested to improve the user interface of the energy exchange whilst ensuring no monopolisation occurs.

Furthermore, the system explored assumes that localised energy market systems can be represented by three elements: electrical energy units, local currency, and users. Each element has been represented in the digital domain. Electrical energy units are represented as ePower tokens, users are represented by wallet addresses and the local currency as eZAR tokens. It is further assumed that users can freely transfer energy among each other; however, traditional power systems lack this infrastructure, with most incorporating passive management systems, analogue devices and unidirectional energy flow. Active power networks such as smart grids are ideal for the system proposed. These modern systems can reliably accommodate bidirectional energy flow and advanced energy management systems. Despite these features, greater involvement in smart contracts will likely be necessary. Some key elements that should be explored are:

1. The application of smart contracts in energy quality regulation
2. The application of smart contracts in the automatic issuing ePower tokens
3. The application of smart contracts in the automatic issuing of eZAR tokens
4. The application of smart contracts in energy transfer

## 5.7 DEVELOPMENT OF A SPECIALISED PEER-TO-PEER BLOCKCHAIN TRADING SYSTEM

### 5.7.1 System Analysis

#### 5.7.1.1 System Overview

A specialised peer-to-peer blockchain trading system has been developed with user interaction achieved through a popular web framework - Flask. Smart contract modelling was used to define the terms of the energy market across various operational scenarios. The smart contract terms were then transformed into computational logic in python. As a result, the system is able reliably regulate crypto asset issuing and autonomously coordinate energy exchange transactions among independent market participants. Furthermore, public node addresses are used to represent energy system stakeholders anonymously, eliminating privacy infringement and network bias risks. Lastly, all historical transaction and market information are stored on the blockchain serving as a reliable and immutable record.

#### 5.7.1.2 System Characteristics

The blockchain displays characteristics of immutability, security and transparency. These characteristics were achieved by integrating a Proof of Work (PoW) algorithm to achieve consensus among independent network miners. As a result, the smart contract parameters were continuously verified and synchronised to present real-time representations of the states of parameters in the energy exchange. These parameters were made available to all network participants, thus enhancing information transparency and accessibility of the electricity market.

#### 5.7.1.3 System Evaluation

The developed blockchain system is further assessed according to the fundamental blockchain design principles portrayed in the original *Bitcoin white paper* [198]. The system proposed for an energy exchange fully complies with these principles as summarised in Tables 5.1 and 5.2.

**Table 5.1.** Blockchain design principles evaluation summary 1

| Design Principle | Evaluation Outcome | Motivation |
|---|---|---|
| Network Integrity | Satisfactory | Transactions are stored on an immutable and distributed blockchain ledger, thus ensuring network honesty, transparency, deliberation and accountability. |
| Distribution of Power | Satisfactory | Distribution of power is achieved by ensuring the network consists of a decentralised network of nodes. Monopolisation of the network is countered through the addition of a consensus algorithm. Furthermore, the blockchain ledger is distributed among all network miners mitigating the risks of single-point network attacks. |
| Privacy | Satisfactory | Public node addresses are used to anonymise energy market participants, thus ensuring participants' privacies are not infringed upon. |
| Network Commitment | Satisfactory | Mass collaboration and network commitment among registered nodes are ensured by providing financial incentives such as ePower token rewards to independent miners for successfully approving and appending a block to the blockchain. These crypto assets can then be exchanged for electricity or eZAR. |

**Table 5.2.** Blockchain design principles evaluation summary 2

| Design Principle | Evaluation Outcome | Motivation |
|---|---|---|
| Security | Satisfactory | The system incorporates mass collaboration of decentralised nodes through a Proof of Work consensus algorithm. The algorithm further performs continuous validatory assessments of the blockchain to detect malicious tampering and synchronise the blockchain. Furthermore, the developed blockchain ensures the longest blockchain is utilised, improving the network's reliability and security. |
| Inclusion | Satisfactory | The blockchain network can accommodate all facets of energy system users. The private blockchain enables registered nodes to interact with the blockchain in a free and secure environment. |

### 5.7.2 Transaction Analysis

All of the transactions, except transaction 6, were valid and successful requests. The unsuccessful transaction can be attributed to excessive harmonic distortion displayed in the submitted power quality report to the blockchain system. The smart contract detected non-compliance to the terms of ePower tokens and acted accordingly by not issuing ePower tokens and notifying the energy producer as depicted in Fig. 4.13. The smart contract was also able to detect compliant conditions as in the cases of transaction 1 (Fig. 4.8) and 3 (Fig. 4.10). Power quality regulation is important as it offers market participants greater reassurance that the energy purchased is compliant with electricity standards and regulations and will not negatively impact their appliances.

The terms of the exchange were effectively translated into computational logic, demonstrated by the system's ability to facilitate exchanges and update relevant account balances autonomously. The transaction information and account balances of users, stored on the blockchain (Fig. 4.8 -4.14) closely reassemble the predicted balances in Table 4.44. Discrepancies can be attributed to the unaccounted transaction fees in the predicted balances. Miners were continuously rewarded for their commitment to the network in the form of ePower tokens with the expense incurred by network participants that initiated transactions in the energy exchange system. The final balances for the three miners are presented in Table 4.46. Furthermore, the system could account for the availability of ePower tokens continuously. Transaction 7 investigated a scenario where the requested ePower exceeded the available ePower. The system effectively accounted for these conditions by splitting the order into valid and invalid transaction components resulting in the order being partially fulfilled, as demonstrated in Fig. 4.14. Evidently, the system captured the characteristics of the smart contract models presented in this study.

### 5.7.3 Study Limitations and Research Opportunities

There are numerous study limitations and areas for improvement that can be identified. Firstly, the scale of the study performed serves as a limitation. The validity of the findings can be improved by incorporating additional nodes in the system. Increasing the scale of the study can result in greater insight into the functional performance of the system by accounting for transaction speeds and competing blockchain synchronisations among miners. Furthermore, a flat gas fee has been incorporated to reward network miners; however, a more adaptive reward scheme can be incorporated in future. One approach may be to evaluate the congestion in transaction requests and adjust the gas fees accordingly to manage the system better. Secondly, transactions are uploaded and mined by the user who initiates the energy exchange due to the system's infrastructure limitations. This approach poses the risk of users not mining transactions onto the blockchain despite the gas reward incentive. A more appropriate approach can be developing a parallel blockchain that can serve as a pool of broadcasted transactions for miners to systematically append to the blockchain network. In addition, the security of the broadcasted transactions can further be improved by incorporating a public-private key pair to encrypt the information of the transactions before being uploaded to the blockchain. Thirdly, the power quality reports are manually submitted to the system by the energy generators, which relies on the assumption that the reports are untampered. This concern can be addressed by directly integrating external data input from smart meters and sensors into the smart contract. Consequently, the risk of data manipulation can be overcome. Lastly, the integration of a smart contract for facilitating the automatic issuing of green certificates is suggested. The certificates can encourage renewable energy participation by energy producers, prosumers and consumers by providing a trustworthy representation of user commitment to their renewable energy goals.

# CHAPTER 6 CONCLUSION AND SCOPE FOR FUTURE WORK

## 6.1 CHAPTER OVERVIEW

This chapter considers the keynotes from various research sub-components. An overview of results, discussions, opportunities for design improvements and future research areas are provided.

## 6.2 INVESTIGATING TRADITIONAL ELECTRICITY MARKET APPROACHES

Electricity markets can be facilitated through various market configurations, such as single-sided and double-sided. The configurations differ in terms of implementation complexity and degree of market power. Single-sided markets offer ease of implementation and uniform price environments. However, these configurations are susceptible to market power abuse. Double-sided markets counter this challenge by accounting for bids and offers from all participants. Furthermore, auction-based operation is recommended over market clearing price (MCP) optimisation due to its continuous trading capabilities and dynamic pricing nature. As a result, greater demand response potential is introduced in auction-based markets. MCP optimisation also has favourable characteristics as it can account for a complete supply and demand balance, whereas auction-based operations cannot. It further enables non-discriminatory price environments by offering uniform prices.

Furthermore, the study's findings are limited to the case studies considered. Further research in adaptive pricing and participant matching strategies is required to mitigate market power abuse risks and promote greater operational efficiency. In doing so, a more fair and reliable electricity market can be realised, leading to greater adoption rates and demand response.

## 6.3 COMPARISON OF POPULAR MACHINE LEARNING TECHNIQUES FOR SHORT-TERM ENERGY FORECASTING

Machine learning in short-term energy forecasting is a promising research field. In this study, different machine-learning algorithms were trained, tested and contrasted for the applications of electricity demand and solar radiation forecasting. The research provides more reliable insight into the average performance of machine learning algorithms in short-term energy forecasting applications. As a result, top-performing forecasting models can be identified. The models investigated in this study were evaluated according to their variance, error quantity and training time requirements for hourly forecasting. The XGB Regressor is found to out-compete 41 other machine-learning models when considering electricity consumption forecasting. It exhibits the highest R-score and lowest RMSE, corresponding to 0.98 and 833.32 MW, respectively. The model's superiority is evident by its RMSE, which is 81.51% lower than the mean. Furthermore, it exhibits a robust training time of 0.23 s, which is 23.87% less than the mean. Similarly, the XGB Regressor is the best-performing model for solar radiance forecasting with an R-score of 0.94, RMSE of 80.22 $\frac{\mathrm{W}}{\mathrm{m}^2}$ and a training time of 1.2 s. The model out-competes the mean R-score, RMSE and training time by 53.13%, 55.33% and 67.13%, respectively.

Furthermore, the study's findings are limited to the data quality, feature selections, validation measures and algorithm parameters. Research suggestions for improving these areas have been provided. Investigating the considered models with real-time data is strongly recommended.

## 6.4 PARTICIPANT MATCHING OPTIMISATION IN ELECTRICITY MARKETS

The optimisation approach proposed demonstrates a scalable and reliable solution to improve participant matching in electricity markets. The strategy can coordinate participants and power flow whilst accounting for power system constraints such as transmission line capacity, generation capacity, demand requirements and existing congestion. The study investigated a diverse range of optimisation approaches suitable for practical implementations. Participant matching through transmission loss and/or transmission congestion is attainable depending on the power system's needs. Preemptive multi-objective optimisation with transmission loss as a priority is recommended when a minimal trade-off is needed.

Furthermore, the study's findings are limited to the accuracy of the optimisation solvers and the data selected for the case study. Consequently, it is recommended that various multi-objective optimisation approaches and scenarios be investigated in future research.

## 6.5 A NOVEL APPROACH TO DYNAMIC PRICING IN ELECTRICITY MARKETS

A novel approach to dynamic pricing has been proposed to address the shortcomings of current pricing schemes employed in conventional electricity markets. The strategy promotes fair and equitable pricing for all market participants whilst accounting for microgrid energy conditions (real-time and forecasted), price volatility, market power, demand response, renewable energy penetration and generation capacity investment. The proposed price strategy has been comprehensively simulated for a case study through MATLAB Simulink. The results demonstrate the stream-line capabilities of the dynamic approach to consider a broad range of external factors and produce robust and adaptive price action for each market participant. The validity of the proposed system can be further investigated through hardware implementation with actual data. As a result, any biases introduced in the case study can be mitigated. Furthermore, various research opportunities arise from this study, with research into future demand response policies to increase consumer price sensitivity strongly recommended.

## 6.6 EXPLORING CONVENTIONAL ETHEREUM SMART CONTRACT SOLUTIONS

A smart contract has been modelled with a generalised framework and deployed on an Ethereum test network. The energy market has been represented in the digital domain to enable smart contract integration. The smart contract demonstrates precise capabilities in facilitating bi-directional energy exchange transactions among three classes of energy ecosystem users (producers, prosumers, and consumers). Different energy users could initiate exchanges such as the sale and resale of ePower tokens through written commands to the smart contract. The status of eZAR and ePower balances are universally accessible along with the contract, demonstrating the system's transparency of the energy exchanges. Ethereum caters for modest smart contract applications but is infeasible for the transaction throughput required in real-time energy markets. Furthermore, the network fees were unsustainable. As a result, developing a specialised blockchain-based system is strongly recommended. Critical limitations to the study are the accuracy of the Ethereum Test network and the centralised configuration of the simulated energy ecosystem. In addition, it suggested that more significant research efforts be focused on integrating smart contracts in smart power networks to cater for more intricate tasks.

## 6.7 DEVELOPMENT OF A SPECIALISED PEER-TO-PEER BLOCKCHAIN TRADING SYSTEM

The study successfully demonstrates an automated, decentralised and regulated peer-to-peer trading system with several transaction scenarios across three categories of market participants - consumers, producers and prosumers. A specialised blockchain network has been used to facilitate a conceptual digital energy market smoothly. The system functions as anticipated and complies with all seven fundamental design principles of blockchains highlighted in the original *Bitcoin White paper*. The blockchain network further encourages energy exchange participation by enhancing the trust in the system through the application of a consensus protocol, removal of intermediaries, integration of smart contracts, and ensuring personal privacy by anonymously representing users by node addresses. In addition, transactions and network participant balances have been stored on the blockchain for enhanced transparency. The system facilitates supply and demand requests for energy modelled as ePower crypto asset tokens. It employs smart contracts to regulate energy transactions among independent power network participants and issue ePower tokens to producers per stipulated power quality regulations. Thus, the blockchain network serves as a neutral and transparent platform enabling users to exchange energy among their peers at their discretion. It further promotes auxiliary power services in traditional active power networks, enhancing decentralised and distributed energy resource management. Various limitations of the developed system have been identified with the following suggestions for improvement provided:

1. Develop a parallel blockchain, serving as a layer two solution, to serve as a pool of broadcasted transactions for miners to systematically append to the blockchain network.
2. Implement an adaptive transaction (gas) fee rate to manage blockchain network congestion better.
3. Incorporate a public-private key pair to encrypt the information of transactions before being uploaded to the blockchain.
4. Utilise smart meters and sensors to provide power quality information directly into the blockchain system.
5. Automatically issue green energy certificates to renewable energy participants through a smart contract.

## 6.8 OVERALL RESEARCH CONCLUDING REMARKS

This research aimed to address the concerns of inequitable electricity markets in smart DC microgrids. The study effectively addresses these concerns through a two-part solution.

The first part considers the efficiency of electricity pricing and participant matching. The shortcomings of current approaches were identified through literature and investigative case studies. A novel dynamic pricing strategy has been developed to mitigate the risks of price volatility and market power abuse seen in current pricing schemes. The strategy achieves these requirements whilst accounting for other factors, such as real-time energy conditions and demand response at increased price space granularity. Furthermore, a multi-objective optimisation scheme has been proposed to improve participant matching by considering transmission loss and congestion minimisation. This scheme enables greater operational efficiencies compared to traditional participant matching approaches. It further considers power system constraints and ensures supply and demand conditions are adequately met.

The second part deals with decentralising electricity market interactions through blockchain technology to further balance market power and enhance trust in the system. A theoretical foundation was constituted through a comprehensive literature review of blockchain technology principles and state-of-the-art. Further insight into the field has been obtained through an exploratory study on a popular blockchain network for smart contract deployment. The study demonstrated that the current blockchain infrastructure is infeasible for the specialised application of facilitating autonomous and decentralised electricity markets. As a result, a specialised blockchain-based energy exchange system has been developed from the first principles to bridge this research gap. The system demonstrates extraordinary efficiency in autonomously coordinating transactions, managing crypto asset token issuing and regulating power quality. The developed technology can achieve these applications whilst operating in a decentralised, transparent and secure environment.

The research aim and goals have been achieved with the research hypotheses accepted. Consequently, the defined research questions have been answered. The study confirms that dynamic pricing can effectively account for a DC microgrid's real-time energy and market conditions. It also proves that energy markets can be facilitated in a decentralised, transparent and secure environment. The research goes a long way towards enhancing deregulated electricity markets in DC microgrids in the future.

Decentralisation of power grids is a promising research avenue when considering the rising demands for energy sector reform and electricity deregulation. The research performed in this dissertation provides a means for decentralisation but is by no means an end. Further research is needed to integrate blockchain technology into smart grids to fully realise autonomous and decentralised power networks. The blockchain system developed in this study can be enhanced to cater for more sophisticated applications related to the control, management and optimisation of electricity systems. A suggested approach may be modelling the smart grids as decentralised autonomous organisations.

# REFERENCES

[1] S. Choudhury, S. Nayak, T. P. Dash, and P. K. Rout, "Overview of DC Microgrid as a Conceivable Future Power System," in *2nd IEEE International Conference on Inventive Communication and Computational Technologies (ICICCT)*, Coimbatore, India, April 20–21, 2018, pp. 1541–1546.

[2] D. Kumar, F. Zare, and A. Ghosh, "DC Microgrid Technology: System Architectures, AC Grid Interfaces, Grounding Schemes, Power Quality, Communication Networks, Applications, and Standardizations Aspects," *IEEE Access*, vol. 5, pp. 12 230–12 256, 2017.

[3] M. F. Zia, M. Nasir, E. Elbouchikhi, M. Benbouzid, J. C. Vasquez, and J. M. Guerrero, "Energy management system for an islanded renewables-based DC microgrid," in *2nd IEEE International Conference on Smart Power and Internet Energy Systems (SPIES)*, Bangkok, Thailand, September 15–18, 2020, pp. 543–547.

[4] T. Debela and A. Bhattacharya, "Design and analysis of a DC/AC microgrid with centralized battery energy storage system," in *43rd Annual Conference of the IEEE Industrial Electronics Society*, Beijing, China, October 29–31, 2017, pp. 8779–8784.

[5] L. I. Dulău, M. Abrudean, and D. Bică, "Effects of Distributed Generation on Electric Power Systems," *Procedia Technology*, vol. 12, pp. 681–686, 2014.

[6] S. Peyghami, P. Palensky, and F. Blaabjerg, "An Overview on the Reliability of Modern Power Electronic Based Power Systems," *IEEE Open Journal of Power Electronics*, vol. 1, pp. 34–50, 2020.

[7] M. Gaiceanu, I. N. Arama, and I. Ghenea, *Power Electronic Converters in AC Microgrid*. Cham, Denmark: Springer International Publishing, 2020, pp. 139–175.

[8] J. A. Sa'Ed, S. Favuzza, F. Massaro, R. Musca, G. Zizzo, A. Cagnano, and E. De Tuglie, "Effects of Demand Side Management on the Operation of an Isolated LV Microgrids," in *IEEE International Conference on Environment and Electrical Engineering (EEEIC)*, Genova, Italy, June 11–14, 2019.

[9] B. K. Ghosh, S. Sen, and S. Chanda, "Intelligent Energy Management Systems for Optimal Techno-Commercial Benefit in DC Micro-grids: A Review," in *Proceedings of 2nd International Conference on VLSI Device, Circuit and System (VLSI DCS)*, Kolkata, India, July 18-19, 2020, pp. 18–19.

[10] G. A. Pagani and M. Aiello, "Generating realistic dynamic prices and services for the smart grid," *IEEE Systems Journal*, vol. 9, no. 1, pp. 191–198, 2015.

[11] G. Dutta and K. Mitra, "A literature review on dynamic pricing of electricity," *Journal of the Operational Research Society*, vol. 68, no. 10, pp. 1131–1145, 2017.

[12] O. Lutz, V. Olavarria, R. Hollinger, C. Wittwer, and B. Koch, "Dynamic tariff design for a robust smart grid concept: An analysis of Global vs. Local incentives," in *IEEE PES Innovative Smart Grid Technologies Conference (ISGT)*, Turin, Italy, September 26–29, 2017, pp. 1–6.

[13] M. Marchesi, "Crypto-Trading: blockchain-oriented energy market," in *AEIT International Annual Conference*, Cagliari, Italy, September 20–22, 2017, pp. 1–5.

[14] G. S. Mahesh, V. Rakesh, S. Mohan, P. Ranjit *et al.*, "Energy management with blockchain technology in dc microgrids," *Materials Today: Proceedings*, vol. 47, pp. 2232–2236, 2021.

[15] L. Raju, A. Swetha, C. K. Shruthi, and J. Shruthi, "IoT based Demand Response Management in Microgrids," in *Proceedings of the 7th International Conference on Electrical Energy Systems (ICEES)*, Chennai, India, February 11–13, 2021, pp. 606–610.

[16] E. M. Malatji, "The use of Dynamic Tariff by The Utilities to Counteract The Influence of Renewable Energy Sources," in *7th IEEE International Conference on Smart Grid*, Newcastle, NSW, Australia, December 9–11, 2019, pp. 103–107.

[17] A. I. Saif and S. K. Khadem, "Consumer-centric electricity market: Review of key european projects," in *17th International Conference on the European Energy Market (EEM)*, Stockholm, Sweden, September 16–18, 2020, pp. 1–6.

[18] K. Qasaymeh and J.-A. K. Van Wyk, "Power to the People? Right of Access to Electricity in South Africa," *Politeia*, vol. 38, no. 2, 2019. [Online]. Available: https://upjournals.co.za/index.php/Politeia/article/view/2727

[19] N. Wamukonya, "Power sector reform in developing countries: mismatched agendas," *Energy Policy*, vol. 31, no. 12, pp. 1273–1289, 2003. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0301421502001878

[20] L. Chinmoy, S. Iniyan, and R. Goic, "Modeling wind power investments, policies and social benefits for deregulated electricity market – A review," *Applied Energy*, vol. 242, pp. 364–377, 2019. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0306261919304970

[21] R. Lu, S. H. Hong, and X. Zhang, "A dynamic pricing demand response algorithm for smart grid: Reinforcement learning approach," *Applied Energy*, vol. 220, pp. 220–230, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261918304112

[22] A. Niromandfam, A. S. Yazdankhah, and R. Kazemzadeh, "Modeling demand response based on utility function considering wind profit maximization in the day-ahead market," *Journal of Cleaner Production*, vol. 251, pp. 1–13, 2020. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0959652619341873

[23] K. Bijuna Kunju and P. N. Rao, "Determination of market clearing price in pool markets with elastic demand," in *15th National Power Systems Conference*, Mumbai, India, December 16–18, 2008.

[24] P. Shinde, I. Boukas, D. Radu, M. Manuel de Villena, and M. Amelin, "Analyzing trade in continuous intra-day electricity market: An agent-based modeling approach," *Energies*, vol. 14, no. 13, 2021. [Online]. Available: https://www.mdpi.com/1996-1073/14/13/3860

[25] H. Chen and L. Han, "Electricity pricing theory based on continuous time commodity model," in *IEEE Power Energy Society General Meeting*, Portland, Oregon, USA, August 5–9, 2018, pp. 1–5.

[26] J. Hu, R. Harmsen, W. Crijns-Graus, E. Worrell, and M. van den Broek, "Identifying barriers to large-scale integration of variable renewable electricity into the electricity market: A literature review of market design," *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 2181–2195, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S136403211730967X

[27] A. E. Kahn, P. Cramton, R. H. Porter, R. D. Tabors *et al.*, "Pricing in the california power exchange electricity market: Should california switch from uniform pricing to pay-as-bid pricing?" *Blue Ribbon Panel Report, California Power Exchange*, 2001.

[28] S. Xu, Y. Zhao, Y. Li, and Y. Zhou, "An iterative uniform-price auction mechanism for peer-to-peer energy trading in a community microgrid," *Applied Energy*, vol. 298, pp. 1–13, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0306261921005390

[29] X. Zou, "Double-sided auction mechanism design in electricity based on maximizing social welfare," *Energy Policy*, vol. 37, no. 11, pp. 4231–4239, 2009. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0301421509003437

[30] M. Khorasany, R. Razzaghi, A. Dorri, R. Jurdak, and P. Siano, "Paving the path for two-sided energy markets: An overview of different approaches," *IEEE Access*, vol. 8, pp. 223 708–223 722, 2020.

[31] D. Shah and S. Chatterjee, "A comprehensive review on day-ahead electricity market and important features of world's major electric power exchanges," *International*

*Transactions on Electrical Energy Systems*, vol. 30, no. 7, 2020. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1002/2050-7038.12360

[32] Y. Bichpuriya and S. Soman, "Electric power exchanges: A review," in *16th National Power Systems Conference*, Mumbai, India, December 15–17, 2010, pp. 115–120.

[33] J. He, X. Xiao, R. Zhong, W. Huang, D. Li, and Q. Chen, "New ac & dc hybrid power supply system and its reliability analysis in data centre," *The Journal of Engineering*, vol. 2019, no. 16, pp. 2800–2803, 2019.

[34] A. Joseph Omosanya, E. Titilayo Akinlabi, and J. Olusegun Okeniyi, "Overview for Improving Steam Turbine Power Generation Efficiency," *Journal of Physics: Conference Series*, vol. 1378, no. 3, pp. 1–8, 2019. [Online]. Available: https://iopscience.iop.org/article/10.1088/1742-6596/1378/3/032040

[35] E. Dogan, M. T. Majeed, and T. Luni, "Revisiting the nexus of ecological footprint, unemployment, and renewable and non-renewable energy for south asian economies: Evidence from novel research methods," *Renewable Energy*, vol. 194, pp. 1060–1070, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148122008254

[36] E. Garcia and H. Liu, "Ilmenite as alternative bed material for the combustion of coal and biomass blends in a fluidised bed combustor to improve combustion performance and reduce agglomeration tendency," *Energy*, vol. 239, pp. 1–14, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544221021617

[37] A. Angelus, "Distributed Renewable Power Generation and Implications for Capacity Investment and Electricity Prices," *Production and Operations Management*, vol. 30, no. 12, pp. 4614–4634, 2021. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1111/poms.13241

[38] A. Ahmed, M. F. Nadeem, A. T. Kiani, and I. Khan, "An overview on optimal planning of distributed generation in distribution system and key issues," in *IEEE Texas Power and Energy Conference (TPEC)*, Texas, USA, February 2–5, 2021, pp. 1–6.

[39] W. Dolega, "Development of electric power network infrastructure in aspect of electric energy supply security – case study poland," *E3S Web of Conferences*, vol. 84, pp. 1–10, 2019.

[40] J. C. Molburg, J. Kavicky, and K. Picel, "The design, construction, and operation of long-distance high-voltage electricity transmission technologies," Argonne National Lab. (ANL), Argonne, IL (United States), Tech. Rep., 2008.

[41] A. Singh, *Electric Power Distribution*. New Delhi, India: Prentice Hall of India, 2017.

[42] G. Mokryani, *Future Distribution Networks*. New York, USA: AIP Publishing, 2022.

[43] O. Majeed Butt, M. Zulqarnain, and T. Majeed Butt, "Recent advancement in smart grid technology: Future prospects in the electrical power network," *Engineering Journal*, vol. 12, no. 1, pp. 687–695, 2021. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S2090447920301064

[44] G. Chicco, "Overview and performance assessment of the clustering methods for electrical load pattern grouping," *Energy*, vol. 42, no. 1, pp. 68–80, 2012. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544211008565

[45] C. K. Lee, K. L. Cheng, and W. M. Ng, "Load characterisation of electric spring," in *IEEE Energy Conversion Congress and Exposition*, Denver, CO, USA, September 15–19, 2013, pp. 4665–4670.

[46] R. Yao and K. Steemers, "A method of formulating energy load profile for domestic buildings in the uk," *Energy and buildings*, vol. 37, no. 6, pp. 663–671, 2005.

[47] J. Wu, Z. Cui, Y. Chen, D. Kong, and Y.-G. Wang, "A new hybrid model to predict the electrical load in five states of australia," *Energy*, vol. 166, pp. 598–609, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360544218320668

[48] K. Malmedal and P. K. Sen, "A better understanding of load and loss factors," in *IEEE Industry Applications Society Annual Meeting*, Edmonton, Canada, USA, October 5–9, 2008, pp. 1–6.

[49] A. Menezes, A. Cripps, R. A. Buswell, J. Wright, and D. Bouchlaghem, "Estimating the energy consumption and power demand of small power equipment in office buildings," *Energy and Buildings*, vol. 75, pp. 199–209, 2014.

[50] F. Alvarado, "The stability of power system markets," *IEEE transactions on power systems*, vol. 14, no. 2, pp. 505–511, 1999.

[51] F. L. Greitzer, R. Podmore, M. Robinson, and P. Ey, "Naturalistic decision making for power system operators," *Journal of Human–Computer Interaction*, vol. 26, no. 2-3, pp. 278–291, 2010.

[52] D. Hazarika and R. Das, "A method for optimal load dispatch of a multi-zone power system with zonal exchange constraints," *Journal of The Institution of Engineers (India): Series B*, vol. 99, no. 2, pp. 97–108, 2018.

[53] X. Xia and A. Elaiw, "Optimal dynamic economic dispatch of generation: A review," *Electric Power Systems Research*, vol. 80, no. 8, pp. 975–986, 2010.

[54] Z. Ming, L. Ximei, and P. Lilin, "The ancillary services in china: An overview and key issues," *Renewable and Sustainable Energy Reviews*, vol. 36, pp. 83–90, 2014.

[55] A. Zecchino, K. Knezović, and M. Marinelli, "Identification of conflicts between transmission and distribution system operators when acquiring ancillary services from electric vehicles," in *IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*. IEEE, Turin, Italy, September 26–29, 2017, pp. 1–6.

[56] S. Chemetova, P. Santos, and M. Ventim-Neves, "Load forecasting in electrical distribution grid of medium voltage," in *Doctoral Conference on Computing, Electrical and Industrial Systems*, Costa de Caparica, Portugal, April 11–13, 2016, pp. 340–349.

[57] H. Guo, Q. Chen, Q. Xia, and C. Kang, "Market power mitigation clearing mechanism based on constrained bidding capacities," *IEEE Transactions on Power Systems*, vol. 34, no. 6, pp. 4817–4827, 2019.

[58] J. A. García and J. D. Reitzes, “International perspectives on electricity market monitoring and market power mitigation,” *Review of Network Economics*, vol. 6, no. 3, 2007.

[59] E. Tómasson, M. R. Hesamzadeh, L. Söder, and D. R. Biggar, “An incentive mechanism for generation capacity investment in a price-capped wholesale power market,” *Electric Power Systems Research*, vol. 189, pp. 1–9, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0378779620305113

[60] P. Cramton and S. Stoft, “A Capacity Market that Makes Sense,” *The Electricity Journal*, vol. 18, no. 7, pp. 43–54, 2005. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S1040619005000850

[61] P. Cramton, A. Ockenfels, and S. Stoft, “Capacity market fundamentals,” *Economics of Energy & Environmental Policy*, vol. 2, no. 2, pp. 27–46, 2013.

[62] S. S. Oren, “Ensuring generation adequacy in competitive electricity markets,” *Policy and Economics*, vol. 1, no. 7, pp. 1–20, 2003.

[63] K. Ju, Q. Wang, L. Liu, and D. Zhou, “Measurement of the price distortion degree for exhaustible energy resources in china: a discount rate perspective,” *Emerging Markets Finance and Trade*, vol. 55, no. 12, pp. 2718–2737, 2019.

[64] P. Shinde and M. Amelin, “A literature review of intraday electricity markets and prices,” in *IEEE Milan PowerTech*, Milan, Italy, June 23–27, 2019, pp. 1–6.

[65] S. Dong, H. Li, F. Wallin, A. Avelin, Q. Zhang, and Z. Yu, “Volatility of electricity price in denmark and sweden,” *Energy Procedia*, vol. 158, pp. 4331–4337, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1876610219308264

[66] D. Xiao, M. K. AlAshery, and W. Qiao, “Optimal price-maker trading strategy of wind power producer using virtual bidding,” *Journal of Modern Power Systems and Clean Energy*, vol. 10, no. 3, pp. 766–778, 2022.

[67] K. R. Abbasi, M. Shahbaz, J. Zhang, M. Irfan, and R. Alvarado, “Analyze the environmental sustainability factors of china: The role of fossil fuel energy and renewable energy,” *Renewable Energy*, vol. 187, pp. 390–402, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148122000763

[68] A. Saavedra, N. A. Galvis, F. Mesa, E. Banguero, M. Castaneda, S. Zapata, and A. J. Aristizábal, “Current state of the worldwide renewable energy generation: a review,” *International Journal on Engineering Applications*, vol. 9, no. 3, pp. 1–15, 2021.

[69] J. Hossain and A. Mahmud, *Renewable energy integration: challenges and solutions*. Gateway East, Singapore: Springer, 2014.

[70] M. J. Blaschke, “Dynamic pricing of electricity: Enabling demand response in domestic households,” *Energy Policy*, vol. 164, pp. 1–10, 2022.

[71] A. R. P. Barusman, T. M. Yuliana, and E. Mirfazli, “Analysis of implementation cost plus pricing method in the decision on the determination of product sales prices,” *International Journal of Advanced Science & Technology*, vol. 29, no. 6, pp. 1832–1838, 2020.

[72] M. E. Cafferky, “Estimating retail breakeven using markup pricing,” *Management Accounting Quarterly*, vol. 18, no. 2, 2017.

[73] K. Indounas, “Successful industrial service pricing,” *Journal of Business & Industrial Marketing*, vol. 24, no. 2, pp. 86–97, 2009.

[74] H. Halimatussakdiah and R. Yuniasih, “Pricing strategies evaluation in radio industry’s firm,” *International Journal of Dynamic Economics and Business*, vol. 4, no. 4, pp. 299–314, 2021.

[75] R. Asgarpour, A. B. Abdul Hamid, and Z. Sulaiman, “A review on customer perceived value and its main components,” *Global Journal of Business and Social Science Review*, vol. 1, pp. 632–640, 2015.

[76] T. Netseva-Porcheva, “Value-based pricing: A success factor in the competitive struggle,” *Marketing*, vol. 42, pp. 227–236, 2011.

[77] H. M. Cannon and F. W. Morgan, “A strategic pricing framework,” *Journal of Services Marketing*, vol. 4, no. 2, pp. 19–30, 1990.

[78] S. Byrne and Y. McCarthy, “Differential Pricing: The Economics and International Evidence,” Central Bank of Ireland, Tech. Rep., 2020. [Online]. Available: https://ideas.repec.org/p/cbi/fsnote/10-fs-20.html

[79] I. Deksnyte and P. Lydeka, “Dynamic pricing and its forming factors,” *International Journal of Business and Social Science*, vol. 3, no. 23, pp. 213–220, 2012.

[80] G. L. Doorman, “Capacity subscription: solving the peak demand challenge in electricity markets,” *IEEE Transactions on Power Systems*, vol. 20, no. 1, pp. 239–245, 2005.

[81] G. Dutta and K. Mitra, “A literature review on dynamic pricing of electricity,” *Journal of the Operational Research Society*, vol. 68, no. 10, pp. 1131–1145, 2017.

[82] S. Simkhada, M. Niraula, P. R. Ojha, Y. Layalu, A. Singh, R. Gwachha, and A. Shrestha, “Time of use electricity pricing in power system planning and operation: Case study of nepalese power system,” *Energy Reports*, vol. 8, pp. 825–831, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352484721012464

[83] M. Nicolson, G. Huebner, and D. Shipworth, “Are consumers willing to switch to smart time of use electricity tariffs? the importance of loss-aversion and electric vehicle ownership,” *Energy Research Social Science*, vol. 23, pp. 82–96, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214629616302961

[84] M. L. Nicolson, M. J. Fell, and G. M. Huebner, “Consumer demand for time of use electricity tariffs: A systematized review of the empirical evidence,” *Renewable and Sustainable Energy Reviews*, vol. 97, pp. 276–289, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032118306257

[85] Q. Zhang, X. Wang, and M. Fu, "Optimal implementation strategies for critical peak pricing," in *6th International Conference on the European Energy Market*, Leuven, Belgium, May 27–29, 2009, pp. 1–6.

[86] H. J. Touma, M. Mansor, M. S. A. Rahman, V. Kumaran, H. B. Mokhlis, Y. J. Ying, and M. Hannan, "Energy management system of microgrid: Control schemes, pricing techniques, and future horizons," *International Journal of Energy Research*, vol. 45, no. 9, pp. 12 728–12 739, 2021.

[87] S. Riyaz, R. Upputuri, and N. Kumar, "Congestion management in power system—a review," *Recent Advances in Power Systems*, vol. 1, no. 1, pp. 425–433, 2021.

[88] F. A. Wolak, "Measuring the benefits of greater spatial granularity in short-term pricing in wholesale electricity markets," *American Economic Review*, vol. 101, no. 3, pp. 247–252, 2011.

[89] G. Poyrazoglu, "Determination of price zones during transition from uniform to zonal electricity market: A case study for turkey," *Energies*, vol. 14, no. 4, pp. 1–13, 2021. [Online]. Available: https://www.mdpi.com/1996-1073/14/4/1014

[90] L. Barroso, T. Cavalcanti, P. Giesbertz, and K. Purchala, "Classification of electricity market models worldwide," in *International Symposium CIGRE*, New Orleans, LA, USA, October 5–7, 2005, pp. 9–16.

[91] C. Sabillon, A. A. Mohamed, B. Venkatesh, and A. Golriz, "Locational marginal pricing for distribution networks: Review and applications," in *IEEE Electrical Power and Energy Conference (EPEC)*, Montreal, QC, Canada, October 16–18, 2019, pp. 1–5.

[92] Q. Lété, Y. Smeers, and A. Papavasiliou, "An analysis of zonal electricity pricing from a long-term perspective," *Energy Economics*, vol. 107, pp. 1–16, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0140988322000366

[93] H. Liu, L. Tesfatsion, and A. Chowdhury, "Locational marginal pricing basics for restructured wholesale power markets," in *IEEE Power and Energy Society General Meeting*, Calgary, AB,

Canada, July 26–30, 2009, pp. 1 – 8.

[94] S. Angra and S. Ahuja, "Machine learning and its applications: A review," in *International Conference on Big Data Analytics and Computational Intelligence (ICBDAC)*, Chirala, Andhra Pradesh, India, March 23–25, 2017, pp. 57–60.

[95] T. Ayodele, *Machine Learning Overview*. London, UK: InTech, 2010.

[96] A. González-Briones, G. Hernández, J. M. Corchado, S. Omatu, and M. S. Mohamad, "Machine learning models for electricity consumption forecasting: A review," in *2nd International Conference on Computer Applications Information Security (ICCAIS)*, Riyadh, Saudi Arabia, May 1–3, 2019, pp. 1–6.

[97] C. Voyant, G. Notton, S. Kalogirou, M.-L. Nivet, C. Paoli, F. Motte, and A. Fouilloy, "Machine learning methods for solar radiation forecasting: A review," *Renewable Energy*, vol. 105, pp. 569–582, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148116311648

[98] V. Nasteski, "An overview of the supervised machine learning methods," *Horizons. B.*, vol. 4, pp. 51–62, 2017.

[99] R. Gentleman and V. J. Carey, "Unsupervised machine learning," in *Bioconductor case studies*. New York, USA: Springer, 2008, pp. 137–157.

[100] J. E. Van Engelen and H. H. Hoos, "A survey on semi-supervised learning," *Machine Learning*, vol. 109, no. 2, pp. 373–440, 2020.

[101] A. Uprety and D. B. Rawat, "Reinforcement learning for iot security: A comprehensive survey," *IEEE Internet of Things Journal*, vol. 8, no. 11, pp. 8693–8706, 2021.

[102] A. K. Lamba, S. Singh, S. Balvinder, N. Dutta, and S. Rela, "Embedding machine & deep learning for mitigating security & privacy issues in iot enabled devices & networks," *International Journal For Technological Research In Engineering*, vol. 7, no. 12, pp. 40–64, 2018.

[103] F. Pallonetto, C. Jin, and E. Mangina, "Forecast electricity demand in commercial building with machine learning models to enable demand response programs," *Energy and AI*, vol. 7, pp. 1–13, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2666546821000690

[104] Z. Camurdan and M. Ganiz, "Machine learning based electricity demand forecasting," in *International Conference on Computer Science and Engineering*, Antalya, Turkey, October 5–8, 2017, pp. 412–417.

[105] M. Belkin, D. Hsu, S. Ma, and S. Mandal, "Reconciling modern machine-learning practice and the classical bias–variance trade-off," *Proceedings of the National Academy of Sciences*, vol. 116, no. 32, pp. 15 849–15 854, 2019.

[106] E. Briscoe and J. Feldman, "Conceptual complexity and the bias/variance tradeoff," *Cognition*, vol. 118, no. 1, pp. 2–16, 2011.

[107] Y. Romitti and I. Sue Wing, "Heterogeneous climate change impacts on electricity demand in world cities circa mid-century," *Scientific reports*, vol. 12, no. 1, pp. 1–14, 2022.

[108] E. Bobbio, S. Brandkamp, S. Chan, P. C. Cramton, D. Malec, and L. Yu, "Resilient electricity requires consumer engagement," Tech. Rep., 2022.

[109] K. Gaur, H. Kumar, R. P. K. Agarwal, K. V. S. Baba, and S. K. Soonee, "Analysing the electricity demand pattern," in *National Power Systems Conference (NPSC)*, Bhubaneswar, India, December 19–21, 2016, pp. 1–6.

[110] T. Vantuch, A. G. Vidal, A. P. Ramallo-González, A. F. Skarmeta, and S. Misák, "Machine learning based electric load forecasting for short and long-term period," in *IEEE 4th World Forum on Internet of Things (WF-IoT)*, Singapore, February 5–8, 2018, pp. 511–516.

[111] I. Shah, F. Jan, and S. Ali, "Functional data approach for short-term electricity demand forecasting," *Mathematical Problems in Engineering*, vol. 1, no. 1, pp. 1–14, 2022.

[112] T. Alquthami, M. Zulfiqar, M. Kamran, A. H. Milyani, and M. B. Rasheed, "A performance comparison of machine learning algorithms for load forecasting in smart grid," *IEEE Access*, vol. 10, pp. 48 419–48 433, 2022.

[113] D. Scott, T. Simpson, N. Dervilis, T. Rogers, and K. Worden, "Machine learning for energy load forecasting," *Journal of Physics: Conference Series*, vol. 1106, pp. 1–6, 2018.

[114] A. Goel and A. Goel, "Regression based forecast of electricity demand of new delhi," *International Journal of Scientific and Research Publications*, vol. 4, no. 9, pp. 1–7, 2014.

[115] R. Porteiro, L. Hernández-Callejo, and S. Nesmachnow, "Electricity demand forecasting in industrial and residential facilities using ensemble machine learning," *Revista Facultad de Ingeniería Universidad de Antioquia*, vol. 1, no. 102, pp. 9–25, 2022.

[116] M. K. M. Shapi, N. A. Ramli, and L. J. Awalin, "Energy consumption prediction by using machine learning for smart building: Case study in malaysia," *Developments in the Built Environment*, vol. 5, pp. 1–14, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S266616592030034X

[117] A. Olabi and M. A. Abdelkareem, "Renewable energy and climate change," *Renewable and Sustainable Energy Reviews*, vol. 158, pp. 1–7, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032122000405

[118] A. A. Jhumka, A. K. Robert T. F., A. Khoodaruth, and C. Ramasawmy, "Comparative performance analysis of solar energy and wind energy systems using rotor angle stability," in *IEEE 7th International Energy Conference (ENERGYCON)*, Riga, Latvia, May 9–12, 2022, pp. 1–5.

[119] B. Raillani, M. Salhi, D. Chaatouf, S. Amraqui, and A. Mezrhab, "Optimization of a porous wind barrier to reduce soiling and avoid shading losses of photovoltaic panels," *Renewable Energy*, vol. 189, pp. 510–523, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0960148122002968

[120] S. R. Das, A. P. Hota, H. M. Pandey, and B. M. Sahoo, “Industrial power quality enhancement using fuzzy logic based photovoltaic integrated with three phase shunt hybrid active filter and adaptive controller,” *Applied Soft Computing*, vol. 121, pp. 1–10, 2022.

[121] K. Sudharshan, C. Naveen, P. Vishnuram, D. V. S. Krishna Rao Kasagani, and B. Nastasi, “Systematic review on impact of different irradiance forecasting techniques for solar energy prediction,” *Energies*, vol. 15, no. 17, pp. 1–39, 2022.

[122] A. Ahmed and M. Khalid, “A review on the selected applications of forecasting models in renewable power systems,” *Renewable and Sustainable Energy Reviews*, vol. 100, pp. 9–21, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1364032118306932

[123] P. Gupta and R. Singh, “Pv power forecasting based on data-driven models: a review,” *International Journal of Sustainable Engineering*, vol. 14, no. 6, pp. 1733–1755, 2021.

[124] I. Jebli, F.-Z. Belouadha, M. I. Kabbaj, and A. Tilioua, “Prediction of solar energy guided by pearson correlation using machine learning,” *Energy*, vol. 224, pp. 1–20, 2021.

[125] L. Huang, J. Kang, M. Wan, L. Fang, C. Zhang, and Z. Zhaoliang, “Solar radiation prediction using different machine learning algorithms and implications for extreme climate events,” *Frontiers in Earth Science*, vol. 9, pp. 1–17, 2021.

[126] L. Gutiérrez, J. Patiño, and E. Duque-Grisales, “A comparison of the performance of supervised learning algorithms for solar power prediction,” *Energies*, vol. 14, no. 15, pp. 1–16, 2021. [Online]. Available: https://www.mdpi.com/1996-1073/14/15/4424

[127] G. Viscondi and S. N. A. Souza, “Solar irradiance prediction with machine learning algorithms: A brazilian case study on photovoltaic electricity generation,” *Energies*, vol. 14, pp. 1–15, 2021.

[128] M. Lima, L. Fernández-Ramírez, P. Carvalho, J. Guimaraes Batista, and D. Freitas, “A comparison between deep learning and support vector regression techniques applied to solar forecast in spain,” *Journal of Solar Energy Engineering*, vol. 144, pp. 1–12, 2021.

[129] C. N. Obiora, A. Ali, and A. N. Hassan, “Predicting hourly solar irradiance using machine learning methods,” in *11th IEEE International Renewable Energy Congress (IREC)*, Hammamet, Tunisia, October 29–31, 2020, pp. 1–6.

[130] M. E. Khondaker and M. Khondaker, “A short term day-ahead solar radiation prediction using machine learning techniques,” *Journal of Climatology Weather Forecasting*, vol. 6, no. 3, pp. 1–5, 2018.

[131] A. Khosravi, R. Koury, L. Machado, and J. Pabon, “Prediction of hourly solar radiation in abu musa island using machine learning algorithms,” *Journal of Cleaner Production*, vol. 176, pp. 63–75, 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959652617330007

[132] A. Fouilloy, C. Voyant, G. Notton, M. L. Nivet, and J. L. Duchaud, “Machine learning methods for solar irradiation forecasting: a comparison in a mediterranean site,” in *International Conference on Energy Engineering and Smart Grids (ESG)*, Cambridge, United Kingdom, June 25–26, 2018.

[133] X. Liu and R. Bansal, “Integrating multi-objective optimization with computational fluid dynamics to optimize boiler combustion process of a coal fired power plant,” *Applied Energy*, vol. 114, pp. 658–669, 2014.

[134] R. C. Bansal and A. F. Zobaa, *Handbook of Renewable Energy Technology Systems*. London, UK: World Scientific Publisher, 2022.

[135] B. Knopf, P. Nahmmacher, and E. Schmid, “The european renewable energy target for 2030 – an impact assessment of the electricity sector,” *Energy Policy*, vol. 85, pp. 50–60, 2015.

[136] J. A. Lesser and X. Su, “Design of an economically efficient feed-in tariff structure for renewable energy development,” *Energy Policy*, vol. 36, no. 3, pp. 981–990, 2008.

[137] S. Heras and J. Palanca, “Smart Grid Demonstration Platform for Renewable Energy Exchange,” *Advances in Practical Applications of Scalable Multi-agent Systems.*, vol. 1, pp. 277–280, 2016.

[138] M. Pilkington, "Blockchain technology: Principles and applications," in *Research handbook on digital transformations*. Cheltenham, UK: Edward Elgar Publishing, 2016, pp. 225–253.

[139] M. Crosby, P. Pattanayak, S. Verma, and V. Kalyanaraman, "Blockchain Technology: Beyond Bitcoin," *Applied Innovation*, vol. 2, no. 6–10, pp. 7–19, 2016.

[140] J. d. Kruijff and H. Weigand, "Understanding the blockchain using enterprise ontology," in *International Conference on Advanced Information Systems Engineering*, Essen, Germany, June 12–16, 2017, pp. 29–43.

[141] R. Lai and D. Lee Kuo Chuen, *Blockchain-From Public to Private*, 1st ed. Massachusetts, USA: Academic Press, 2018, vol. 2.

[142] S. S. Sabry, N. M. Kaittan, and I. M. Ali, "The road to the blockchain technology: Concept and types," *Periodicals of Engineering and Natural Sciences*, vol. 7, no. 4, pp. 1821–1832, 2019.

[143] A. I. Abdi, F. E. Eassa, K. Jambi, K. Almarhabi, and A. S. A. M. Al-Ghamdi, "Blockchain platforms and access control classification for iot systems," *Symmetry*, vol. 12, no. 10, pp. 1–17, 2020.

[144] D. Tapscott, D. Ticoll, and A. Lowy, *Blockchain Revolution: How the Technology Behind Bitcoin Is Changing Money, Business, and the World*. London, England: Penguin Publishing Group, 2016.

[145] S. Gupta, S. Sinha, and B. Bhushan, "Emergence of Blockchain Technology: Fundamentals, Working and its Various Implementations," in *Proceedings of the International Conference on Innovative Computing & Communications (ICICC)*, Delhi, India, February 21–23, 2020, pp. 1–5.

[146] Y. Zhao, "Research on the Consensus Mechanisms of Blockchain Technology," in *International Conference on Economics, Finance, Business, and Development (ICEFBD)*, Xiamen, China, October 19–21, 2018, pp. 289–293.

[147] A. Banafa, *Blockchain Technology and Applications*. Gistrup, Denmark: River Publishers, 2022.

[148] Q. Feng, D. He, S. Zeadally, M. K. Khan, and N. Kumar, "A survey on privacy protection in blockchain system," *Journal of Network and Computer Applications*, vol. 126, pp. 45–58, 2019.

[149] Y. He, H. Li, X. Cheng, Y. Liu, C. Yang, and L. Sun, "A Blockchain Based Truthful Incentive Mechanism for Distributed P2P Applications," *IEEE Access*, vol. 6, no. 1, pp. 27 324–27 335, 2018.

[150] N. D. Bhaskar and D. L. K. Chuen, *Bitcoin Mining Technology*. Massachusetts, USA: Academic Press, 2015.

[151] H. Halpin and M. Piekarska, "Introduction to security and privacy on the blockchain," in *2nd IEEE European Symposium on Security and Privacy Workshops, EuroS and PW*, Paris, France, April 26–28, 2017, pp. 1–3.

[152] B. Preneel, "Cryptographic hash functions," *European Transactions on Telecommunications*, vol. 5, pp. 431 – 448, 2010.

[153] S. Sabah, N. Mahdi, and I. Majeed, "The road to the blockchain technology: Concept and types," *Periodicals of Engineering and Natural Sciences (PEN)*, vol. 7, pp. 1821–1832, 2019.

[154] D. Rachmawati, J. Tarigan, and A. Ginting, "A comparative study of message digest 5 (md5) and sha256 algorithm," *Journal of Physics: Conference Series*, vol. 978, no. 1, pp. 1–6, 2018.

[155] M. Nofer, P. Gomber, O. Hinz, and D. Schiereck, "Blockchain," *Business Information Systems Engineering*, vol. 59, no. 3, pp. 183–187, 2017.

[156] Q. Zhou, H. Huang, Z. Zheng, and J. Bian, "Solutions to scalability of blockchain: A survey," *IEEE Access*, vol. 8, pp. 16 440–16 455, 2020.

[157] S. Sabah, N. Mahdi, and I. Majeed, “The road to the blockchain technology: Concept and types,” *Periodicals of Engineering and Natural Sciences (PEN)*, vol. 7, pp. 1821–1832, 2019.

[158] M. Pilkington, “Blockchain technology: Principles and applications,” in *Research handbook on digital transformations*. Camberley, UK: Edward Elgar Publishing, 2016, pp. 225–253.

[159] Z. Zheng, S. Xie, H.-N. Dai, X. Chen, and H. Wang, “Blockchain challenges and opportunities: A survey,” *International Journal of Web and Grid Services*, vol. 14, no. 4, pp. 352–375, 2018.

[160] Y. Huang, Y. Bian, R. Li, J. L. Zhao, and P. Shi, “Smart contract security: A software lifecycle perspective,” *IEEE Access*, vol. 7, pp. 150 184–150 202, 2019.

[161] N. Szabo, “Smart Contracts : Building Blocks for Digital Transformation,” *The Journal of Transhumanist Thought*, vol. 16, pp. 1–14, 1996.

[162] S. Sayeed, H. Marco-Gisbert, and T. Caira, “Smart Contract: Attacks and Protections,” *IEEE Access*, vol. 8, pp. 24 416–24 427, 2020.

[163] Z. Zheng, S. Xie, H. N. Dai, W. Chen, X. Chen, J. Weng, and M. Imran, “An overview on smart contracts: Challenges, advances and platforms,” *Future Generation Computer Systems*, vol. 105, pp. 475–491, 2020.

[164] L. Ante, “Smart contracts on the blockchain – A bibliometric analysis and review,” *Telematics and Informatics*, vol. 57, pp. 1–29, 2020.

[165] S. Wang, Y. Yuan, X. Wang, J. Li, R. Qin, and F.-Y. Wang, “An overview of smart contract: architecture, applications, and future trends,” in *IEEE Intelligent Vehicles Symposium (IV)*, Changshu, China, June 26–30, 2018, pp. 108–113.

[166] W. Zou, D. Lo, P. S. Kochhar, X. B. D. Le, X. Xia, Y. Feng, Z. Chen, and B. Xu, “Smart Contract Development: Challenges and Opportunities,” *IEEE Transactions on Software Engineering*, vol. 47, no. 10, pp. 2084–2106, 2021.

[167] C. Sillaber and B. Waltl, "Life Cycle of Smart Contracts in Blockchain Ecosystems," *Datenschutz und Datensicherheit (DuD)*, vol. 41, no. 8, pp. 497–500, 2017.

[168] A. Hirsch, Y. Parag, and J. Guerrero, "Microgrids: A review of technologies, key drivers, and outstanding issues," *Renewable and Sustainable Energy Reviews*, vol. 90, pp. 402–411, 2018.

[169] L. Wang, S. Jiao, Y. Xie, S. Mubaarak, D. Zhang, J. Liu, S. Jiang, Y. Zhang, and M. Li, "A permissioned blockchain-based energy management system for renewable energy microgrids," *Sustainability (Switzerland)*, vol. 13, no. 3, pp. 1–19, 2021.

[170] A. Saxena, R. Kumar, R. C. Bansal, and M. Mahmud, "Bidding strategies of a power producer in power market: measurement indices and evaluation," in *Uncertainties in Modern Power Systems*. Massachusetts, USA: Academic Press, 2021, pp. 635–652.

[171] Y. Shang, M. Liu, Z. Shao, and L. Jian, "Internet of smart charging points with photovoltaic Integration: A high-efficiency scheme enabling optimal dispatching between electric vehicles and power grids," *Applied Energy*, vol. 278, pp. 1–16, 2020.

[172] O. Núñez-Mata, R. Palma-Behnke, F. Valencia, P. Mendoza-Araya, and G. Jiménez-Estévez, "Adaptive protection system for microgrids based on a robust optimization strategy," *Energies*, vol. 11, no. 2, 2018.

[173] M. Mohammadi, Y. Noorollahi, B. Mohammadi-ivatloo, and H. Yousefi, "Energy hub: From a model to a concept – A review," *Renewable and Sustainable Energy Reviews*, vol. 80, pp. 1512–1527, 2017.

[174] A. Heidari, R. C. Bansal, J. Hossain, and J. Zhu, "Strategic risk aversion of smart energy hubs in the joined energy markets applying a stochastic game approach," *Journal of Cleaner Production*, vol. 349, pp. 1–15, 2022.

[175] A. Heidari and R. C. Bansal, "Probabilistic correlation of renewable energies within energy hubs for cooperative games in integrated energy markets," *Electric Power Systems Research*, vol. 199, pp. 1–13, 2021.

[176] 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, 2018.

[177] M. Foti and M. Vavalis, "Blockchain based uniform price double auctions for energy markets," *Applied Energy*, vol. 254, pp. 1–11, 2019.

[178] E. Mengelkamp, J. Gärttner, K. Rock, S. Kessler, L. Orsini, and C. Weinhardt, "Designing microgrid energy markets: A case study: The Brooklyn Microgrid," *Applied Energy*, vol. 210, pp. 870–880, 2018.

[179] L. Aniello, R. Baldoni, E. Gaetani, F. Lombardi, A. Margheri, and V. Sassone, "A prototype evaluation of a tamper-resistant high performance blockchain-based transaction log for a distributed database," in *13th European Dependable Computing Conference (EDCC)*, Geneva, Switzerland, September 4–8, 2017, pp. 151–154.

[180] L. Ql, X. Li, B. Qi, and H. Wang, "Shared economy model of charging pile based on block chain ecosystem," *Electric Power Construction*, vol. 38, no. 9, pp. 1–7, 2017.

[181] M. Mihaylov, S. Jurado, K. Van Moffaert, N. Avellana, and A. Nowé, "NRG-X-change a novel mechanism for trading of renewable energy in smart grids," in *3rd International Conference on Smart Grids and Green IT Systems*, Barcelona, Spain, April 3–4, 2014, pp. 101–106.

[182] V. Brilliantova and T. W. Thurner, "Blockchain and the future of energy," *Technology in Society*, vol. 57, pp. 38–45, 2019.

[183] X. Wu, B. Duan, Y. Yan, and Y. Zhong, "M2M blockchain: The case of demand side management of smart grid," in *International Conference on Parallel and Distributed Systems (ICPADS)*, Sentosa, Singapore, December 11–13, 2018, pp. 810–813.

[184] S. Noor, W. Yang, M. Guo, K. H. van Dam, and X. Wang, "Energy Demand Side Management within micro-grid networks enhanced by blockchain," *Applied Energy*, vol. 228, pp. 1385–1398, 2018.

[185] J. J. Sikorski, J. Haughton, and M. Kraft, "Blockchain technology in the chemical industry: Machine-to-machine electricity market," *Applied Energy*, vol. 195, pp. 234–246, 2017.

[186] R. Mulla, "Hourly energy consumption," 2018. [Online]. Available: https://www.kaggle.com/datasets/robikscube/hourly-energy-consumption?resource=download

[187] S. VCH, "Investigating solar radiation," 2017. [Online]. Available: https://www.kaggle.com/code/sarahvch/investigating-solar-radiation/data

[188] P. Klement, T. Brandt, L. Schmeling, A. A. de Bronstein, S. Wehkamp, F. A. Penaherrera Vaca, M. Lanezki, P. Schönfeldt, A. Hill, and N. Katic, "Local energy markets in action: Smart integration of national markets, distributed energy resources and incentivisation to promote citizen participation," *Energies*, vol. 15, no. 8, pp. 1–24, 2022.

[189] U. Damisa, N. I. Nwulu, and P. Siano, "Towards blockchain-based energy trading: A smart contract implementation of energy double auction and spinning reserve trading," *Energies*, vol. 15, no. 11, pp. 1–16, 2022.

[190] 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, 2022.

[191] T. Górski, "Reconfigurable smart contracts for renewable energy exchange with re-use of verification rules," *Applied Sciences*, vol. 12, no. 11, pp. 1–21, 2022.

[192] M. Hougan and D. Lawant, *Cryptoassets: The Guide to Bitcoin, Blockchain, and Cryptocurrency for Investment Professionals*. New York, USA: CFA Institute Research Foundation, 2021.

[193] C. Dannen, *Introducing Ethereum and Solidity*. Berkeley, CA, USA: Apress, 2017.

[194] N. Sánchez-Gómez, J. Torres-Valderrama, M. M. Risoto, and A. Garrido, "Blockchain Smart Contract Meta-modeling," *Journal of Web Engineering*, vol. 20, no. 7, pp. 2059–2080, 2021.

[195] V. Anilkumar, J. A. Joji, A. Afzal, and R. Sheik, “Blockchain simulation and development platforms: survey, issues and challenges,” in *International Conference on Intelligent Computing and Control Systems (ICCS)*. IEEE, Madurai, India, May 15–17, 2019, pp. 935–939.

[196] C. Devi Parameswari and M. Ilayaraja, “Decentralized public distribution system on the ethereum blockchain interact with myetherwallet,” in *Blockchain and Deep Learning*. Berlin, Germany: Springer, 2022, pp. 107–124.

[197] N. R. Naraindath, R. C. Bansal, and R. M. Naidoo, “The uprising of blockchain technology in the energy market industry,” in *International Conference on Recent Developments in Electrical and Electronics Engineering (ICRDEEE)*, Faridabad, India, April 15–16, 2022.

[198] C. S. Wright, “Bitcoin: A Peer-to-Peer Electronic Cash System,” *SSRN Electronic Journal*, vol. 1, no. 1, 2008.