A Clustered Small Community Based Novel Electricity Trade Model for Consumers

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Abstract

The economic development of Bangladesh is increasing day by day where electricity plays as a vital infrastructural input for economic development. In modern life, electricity is the flexible form of energy and also part of critical resource. The extensive demand for electricity can be observed in all economics, households and companies. There are such important factors such as industrialization, extensive urbanization, population growth, rising standard of living and even the modernization of the agricultural sector which are solely responsible for the extensive demand of electricity. Furthermore, the extensive use of electronic home appliance and gadgets has caused a significant increase in household electricity usage, leading to difficulties such as rising energy expenses and intricate pricing systems. This problem is especially noticeable in nations such as Bangladesh, where the increasing middle class increases demand. The existing price system, which includes progressive tariff tiers, unfairly impacts those with lesser incomes, and the fluctuating energy usage during different seasons adds further financial pressure. To tackle these difficulties, it is necessary to employ inventive approaches, such as reevaluating pricing models, investigating energy-saving technologies, and executing community-driven projects. The proposed solution entails integrating a billing system within a time series forecasting framework to create an innovative electricity trading model. The main objective is to minimize the expenses associated with energy consumption while maintaining the same power usage level, providing an opportunity for consumers with lower consumption to generate cash. The primary objective of this strategic approach is to mitigate economic hardships, enhance equity, and cultivate reciprocal advantages within the energy sector. The essential participants in this endeavor encompass users/consumers, distributors, a smart meter system, and a consolidated billing system. The primary focus is to uphold privacy, instill trust in billing, and ensure meter reading and measurement security. This establishes a fair and safe framework for electricity trading, promoting a sustainable energy future.

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Chapter 1

Introduction

Customers are witnessing a consistent increase in household power consumption due to the extensive usage of electrical and technological devices. Due to the extensive use of these devices, electricity consumption is continuously rising. However, it is common for energy usage to exceed the higher tariff thresholds, resulting in the consumer paying a more significant amount corresponding to the higher threshold, even if the electricity consumption only slightly exceeds that threshold. In certain seasons, like summer or winter, energy usage increases, resulting in higher costs due to elevated tariff rates [1]. Regarding power usage, the increased tariff rate incurs a considerably greater cost than the prior rate, which is the primary issue that needs attention. To address this issue, a revolutionary power trading scheme is suggested, wherein consumers will engage in a billing system that ensures enhanced security.

1.1 Research Motivation

Due to new improvements in technology and the use of electronic devices, there has been a rise in household power consumption. This use of technology can be clarified by the general adoption of several electronic devices that have become essential in our everyday lives, such as mobile phones, computers, air conditioners, and home amusement systems. Nevertheless, the increasing need for electricity has presented challenges such as escalating energy expenses and the complexities of comprehending pricing mechanisms [2]. The global power demand has significantly increased due to the increasing use of smart appliances and digital entertainment systems. Bangladesh, renowned for its swift urbanization and burgeoning middle class, has witnessed a notably substantial surge in the utilization of electronic gadgets. Energy consumption has grown essential as the country advances towards industrialization and economic growth. Nevertheless, the rapid escalation in electrical energy consumption is causing apprehension regarding its long-term viability and economic repercussions—the escalating energy usage results in a severe consequence - the recurrent exceeding of higher-priced tariff brackets. Electricity tariffs are divided into progressive tiers, where rates increase when consumption surpasses specific limits. Although the primary objective of this pricing structure is to promote energy conservation, it often places an inequitable burden on customers. Even a slight increase in consumption might significantly increase the total cost of electricity bills. This situation is particularly relevant in Bangladesh, where a substantial share of the population is in the lower-income bracket. The unequal effect of increasing tariff brackets on these households worsens economic inequalities and raises issues about social fairness. Furthermore, the variations in energy consumption throughout the year, especially during the sweltering summers and frigid winters, worsen individuals' financial hardships. Using cooling and heating devices, such as AC and electric heaters, continuously contributes to the boosted electricity consumption during this period. Therefore, individuals are compelled to allocate a more significant portion of their financial resources to cover the escalated electricity costs, exacerbating the burden on their household budgets. Uncovering inventive and unique approaches to tackle the difficulties and alleviate the economic strain on folks is essential. A novel strategy that is at the forefront of programs designed for the deployment of residential electricity usage and payment. The fundamental basis of the proposed solution lies in creating an electricity trading system which will benefit both high and low level electricity consumers. This solution guarantees the secure and transparent documentation of electricity usage and its corresponding expenses. The energy usage of every consumer is precisely documented in an unalterable digital ledger, eliminating the possibility of incorrect billing or manipulation. The increased transparency fosters trust and confidence among consumers, essential aspects in an industry where financial transactions are generally viewed with doubt. Moreover, the proposed trading system can be introduced with the concept of peer-to-peer energy exchange among customers. This innovative concept facilitates the seamless transmission of excess energy from one household to another within the same network. For instance, a residence outfitted with solar panels can easily share surplus energy with neighbors facing power shortages. The transition from a conventional, centralized energy distribution model to a decentralized, community-focused approach has extensive implications. It enhances energy efficiency and cultivates a sense of collaboration and collective accountability among consumers, ultimately alleviating pressure on the national power system. The user's text is simply a backslash character. In Bangladesh, where the electrical generation and distribution facilities encounter persistent difficulties, implementing the proposed trading plan offers a compelling and viable alternative. By harnessing the proposed trading plan, the country may surpass the constraints imposed by conventional energy distribution methods and make substantial strides toward attaining sustainable and fair energy usage. The increasing energy consumption in Bangladesh is in line with a global pattern driven by technical progress and shifts in lifestyle. These issues encompass financial burdens associated with elevated tariff levels and swings in demand throughout the year, necessitating the implementation of innovative remedies. An optimistic option involves the implementation of the proposed electricity trading initiative, which exhibits substantial promise in tackling these problems. This novel strategy has the potential to revolutionize energy consumption habits, foster communal collaboration, and contribute to a more sustainable energy future for Bangladesh by implementing a dependable and transparent billing system and facilitating direct energy exchange among individuals.

1.2 Objectives and Contributions

The main objective of the proposed novel trading model is to reduce the energy consumption cost of the consumer without lowering their electricity consumption and also provide a way to have a money-earning scope for those kinds of consumers whose electricity consumption is relatively lower than the others. The possible outcome of this research is to provide benefits for higher and lower-consumed consumers. Concurrently, the model introduces an avenue for individuals with comparatively lower energy consumption to generate additional income. This equitable approach seeks to bestow advantages upon high and low-energy consumers, fostering a harmonious and inclusive energy landscape. The objectives of this examination are to decrease the monetary expense coming about because of rising energy costs and permit people who use less energy to receive the benefits of their environmentally friendly activities. The primary objective of this theoretical structure is to create conditions that empower both gatherings of customers to benefit from their choices regarding energy utilization.

- **Cost Reduction without Consumption Reduction:** The core proposition of the model centers on the notion that consumers can effectively reduce their energy expenses without resorting to energy austerity. By capitalizing on proposed energy trading plan, surplus energy can be channeled within the local network, offsetting costs for all participants.
- **Empowering Low Consumers:** Traditional billing structures disproportionately impact lower energy consumers. This model rectifies the disparity by enabling households with lower energy footprints to monetize their energy conservation efforts, effectively turning their efficient habits into a revenue stream.
- **Promoting Energy Equity:** The model fosters a sense of fairness by mitigating the financial discrepancies arising from escalating tariff slabs. It engenders an environment where consumers, irrespective of their energy consumption levels, can benefit from participating in the energy trading network.
- **Community-Centric Energy Management:** The trading model introduces a collaborative dimension to energy distribution. Surplus energy generated by one household can be seamlessly shared with neighbors facing energy deficits, creating a symbiotic energy ecosystem that reduces strain on the national grid.

- **Sustainable Energy Future:** By incentivizing energy efficiency and promoting a culture of responsible energy consumption, this model contributes to a sustainable energy future. It encourages consumers to adopt eco-friendly practices while concurrently fostering economic growth.

A typical electricity trading system among the distributor and consumers are depicted bellow:

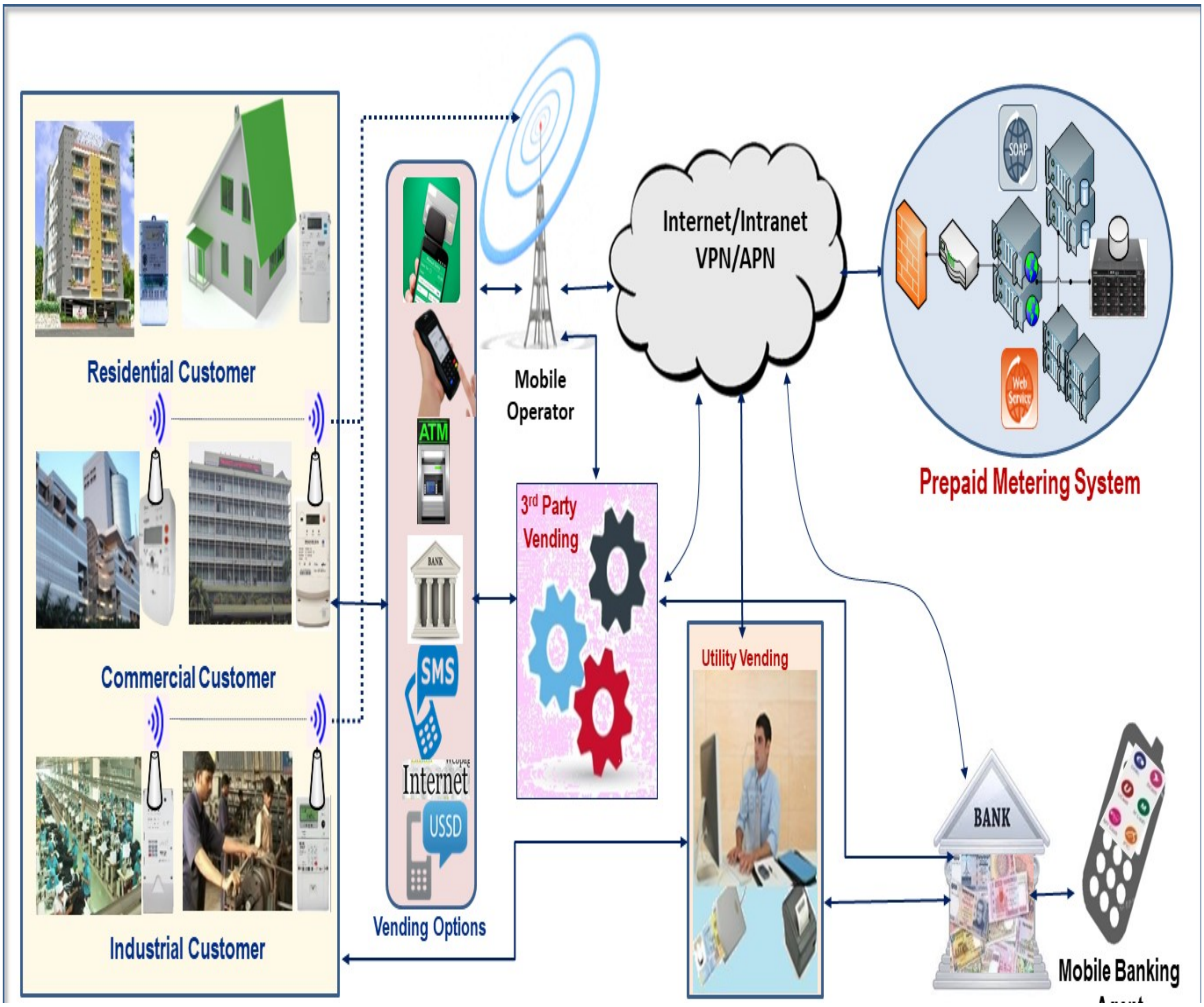

Figure 1.1: Existing Electricity Trading System

In the proposed trading model, we used real data of a renowned community of the capital Dhaka city of Bangladesh and developed the novel electricity trading plan among the lower and higher electricity consumers where both parties will have definite sort of monetary advantages as well as the electricity consumption will be more optimized. Ultimately, the innovative trading model surpasses the traditional limitations of energy usage, presenting a revolutionary method that connects both high and low-energy users. This model lessens the economic strain on households and prepares for a more equitable and environmentally friendly energy system. The proposed clustered small community based novel electricity trade model is depicted bellow:

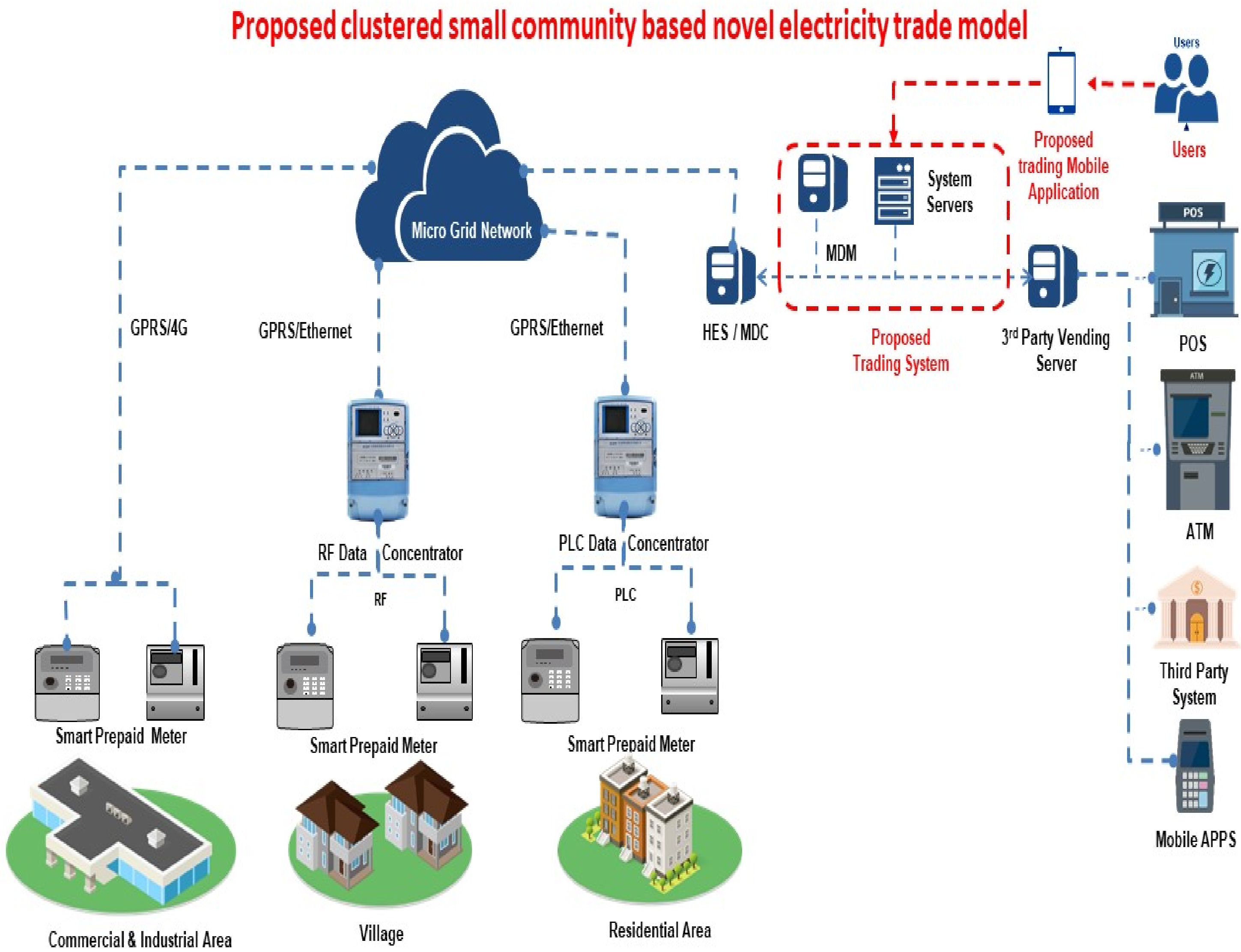

Figure 1.2: Proposed Electricity Trading System

Chapter 2

Background

In the contemporary realm of energy management and utilization, there exists a necessity to integrate advanced technologies to attain efficiency and sustainability. Intelligent electricity meter systems represent a significant shift in how we observe and utilize electricity. Such systems facilitate the provision of real-time information regarding electricity consumption, thereby aiding consumers and utility providers in making more informed decisions. Furthermore, microgrid systems are a vital concept that enables localized and frequent renewable energy generation, distribution, and utilization. These microgrids promote energy independence and resilience, aligning with the current trend toward decentralized power networks. Predictive modeling is crucial in optimizing these systems' potential benefits. For example, the ARIMA time series model can accurately predict a customer's monthly electricity usage. This predictive ability empowers users to plan and adjust their energy consumption, contributing to energy conservation. The Branch and Bound state space tree algorithm is a handy tool to minimize trading and distributing energy costs. By thoroughly exploring different options, this algorithm can find the most cost-effective paths in the complex network of energy transactions. Integrating intelligent meter systems, microgrid technologies, predictive models, and algorithmic optimization is something for a more adaptable, sustainable electricity ecosystem.

2.1 Time Series Analysis and Forecasting

Time series forecasting is a specialized field in statistical analysis focusing on predicting future data points in a sequential dataset, where each observation is arranged chronologically. The salient characteristic of this domain resides in its emphasis on modeling temporal interactions to capture patterns and trends in the data. Time series forecasting has diverse academic disciplines and practical situations, ranging from economics, finance, and environmental science to epidemiology and meteorology. By examining past data and identifying underlying patterns in time series data, individuals can acquire valuable insights that can inform informed decision-making and strategic planning [3].

The underlying idea of the foundation of time series forecasting is the presumption of temporal dependence. This means that each data point is influenced by its previous values and, in certain instances, by repeating patterns. Time series forecasting can be divided into three main components: trend, seasonality, and noise. The trend component denotes the extended and organized variations in the data over a lengthy period. In contrast, seasonality captures the regular and brief oscillations often associated with calendar or environmental conditions. The noise component refers to the irregular and unpredictable changes that naturally exist in real-world data. Developing good forecasting models requires a thorough comprehension and precise modeling of these components.

The strategies used in time series forecasting range from traditional statistical techniques to sophisticated machine learning systems. ARIMA models are commonly used due to their ability to incorporate temporal dependencies and non-stationarity in the data. Time series forecasting is an ongoing research topic in academia, where scientists continuously improve existing methodologies and explore new ways. The challenges researchers in this field focus on include data preprocessing, model selection, and performance evaluation. The latter frequently entails employing a range of statistical parameters, like mean squared error (MSE), mean absolute percentage error (MAPE), and root mean squared error (RMSE), to evaluate the precision and dependability of forecasting models. Moreover, the utilization of time series forecasting in particular areas, such as predicting energy demand [4], forecasting stock market trends, or modeling epidemics, enhances the depth of scholarly discussions and broadens the range of the discipline. Given the increasing amount and intricacy of time series data in different industries, it is crucial to develop and improve forecasting methods continuously. This is necessary to assist decision-makers and enhance the accuracy of time series models, ensuring their ongoing significance and usefulness in academia and other fields.

2.2 ARIMA (AutoRegressive Integrated Moving Average)

ARIMA (AutoRegressive Integrated Moving Average) is an approach used for analyzing and forecasting data demonstrating distinct time series elements. This technique principally finds its usage where noticeable temporal patterns emerge, such as stock market prices, economic indices, or meteorological trends, amongst other forms [5]. ARIMA's methodology integrates three crucial components: namely AutoRegression (AR), Integration (I) along with Moving Averages (MA)."

2.2.1 AutoRegressive (AR) Component

The Autoregressive (AR) element is the correlation between a time series' existing value and its historical data. It's presumed that the present measurement linearly relies on previous ones. In an AR(p) model, 'p' signifies utilizing past p pieces of observation to foresee the impending number in this sequence.

2.2.2 Integrated (I) Component

The combined element emphasizes differentiating chronological data to achieve a stationary state. Stationarity is a pivotal assumption in various time series models because it streamlines model development and frequently results in enhanced predictions. The process of differencing entails deducting preceding observations from present ones. How many iterations it takes to reach stability through this procedure is represented by the 'order of differencing' (d).

2.2.3 Moving Average (MA) Component

The Moving Average (MA) element is charged with understanding the interconnection between the existing value and previously predicted flaws. It frames how present values depend on an amalgamation of recent forecasting inaccuracies linearly. A model denoted as MA(q) utilizes earlier q prediction mistakes to anticipate successive values in a chain.

Combining these three components, an ARIMA(p, d, q) model can be represented as follows:

$$Y(t) = \mathrm{AR}(p) + \mathrm{I}(d) + \mathrm{MA}(q) + \epsilon(t) \tag{2.1}$$

Y(t): The value of the time series at a time 't'.

AR(p): AutoRegressive component using the previous 'p' observations.

I(d): Integrated component involving differencing the data 'd' times to achieve stationarity.

MA(q): Moving Average component using the previous 'q' forecast errors.

$\epsilon(t)$**:** Random noise or error term at time t.

Steps in Building an ARIMA Model:

Data Preparation: Clean the data, handle missing values, and ensure a consistent time interval between observations.

Stationarity: Check for stationarity and apply differencing if needed to make the series stationary.

ACF and PACF: Execute the plotting of both AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF). This procedure will assist in identifying 'p' for AR, as well as 'q' for MA components.

Model Selection: Choose appropriate values of 'p', 'd', and 'q' based on the ACF and PACF plots, as well as other statistical criteria.

Model Estimation: Estimate the model parameters using algorithms like maximum likelihood estimation.

Model Diagnostic: Check the residuals for any patterns or correlations that might suggest model inadequacies.

Forecasting: It uses the fitted ARIMA model to make forecasts for future time points pridictions.

ARIMA is a powerful and widely used tool, but it may only be suitable for some types of time series data. Some complex or nonlinear patterns require more advanced models, such as SARIMA (Seasonal ARIMA) or other machine-learning approaches.

2.3 Smart Electricity Meter System

A Smart Power Meter System is an innovative technology that improves the monitoring, measuring, and management of power usage in various contexts, including residences and companies [6]. Digital meters replace analog meters with multiple capabilities that enhance efficiency, precision, and data gathering. The main characteristics of a Smart Electricity Meter System are:

2.3.1 Real-time Data and Bidirectional Communication

Intelligent meters utilize digital technology to measure power consumption, providing enhanced precision compared to traditional analog meters. This leads to improved accuracy in billing and data on usage. Smart meters provide real-time electricity usage data that is accessible to both consumers and utility providers. This enables enhanced surveillance of consumption patterns and load control. The distinguishing feature of smart meters is their capacity to communicate in both directions. They can automatically transmit consumption data to utility providers, reducing the need for manual meter readings. In addition, utility companies can transmit data to meters from a distant location. This includes sending updates, pricing adjustments, and demand-response signals [7].

2.3.2 Remote Monitoring and Energy Management

Intelligent metering systems are valuable for service providers and clients to monitor energy consumption remotely. These units offer multiple benefits, including detecting anomalies, identifying problems precisely, and optimizing power use. Through the provision of real-time data, users are enabled to make informed decisions regarding their electricity usage patterns. Users can adjust their usage patterns during periods of high demand to reduce costs while monitoring the success of their techniques for conserving power consumption [8]. In addition to these benefits provided by smart meters, there is the feature of time-sensitive pricing. This adjusts the cost of electricity based on the different daylight hours, which affects users' inclination to shift their activities away from peak times when there are strict deadlines. This helps to alleviate strain on the power grid during periods of high demand, whether during the day or at night. Furthermore, utility companies acquire authority over dispatch signals linked to smart meters, limiting electricity reduction during situations characterized by high demand. This helps to prevent system blackouts that are likely to occur during periods of maximum load.

2.3.3 Improved Billing and Integration with Smart Grid

Smart meters provide accurate automated readings that significantly reduce billing errors and disputes. Users get access to comprehensive billing data based on their actual consumption. The fundamental components of a broader innovative grid framework encompass these advanced meters, integrating sophisticated technology to improve the electricity system's resilience, sustainability, and effectiveness. Due to the complex nature of the data collected by intelligent metering, it is crucial to protect this information from unauthorized access. Therefore, extra security standards must be implemented to ensure that consumer details remain appropriately safeguarded [8]. An Intelligent Electricity Meter Program offers numerous benefits, such as improved energy monitoring, reduced operational costs for utility companies, increased billing accuracy, and a more reliable electrical system.

2.4 Microgrid System

The effective execution of the trading model largely depends on incorporating a Microgrid System [9]. A Microgrid System is a self-contained energy system capable of autonomously generating, distributing, and controlling electricity in conjunction with or separate from the primary power grid. The system comprises several distributed energy resources (DERs), including solar panels, wind turbines, battery storage, and backup generators, all operating in synergy to guarantee a dependable and robust power provision. The implementation of a microgrid system into the trading model yields several benefits. An outstanding advantage is the ability to generate power on-site using sustainable resources such as solar and wind, contributing to the reduction in dependence on traditional fossil fuel-derived energy sources. Within the framework of the trading model, a microgrid system presents numerous significant benefits:

2.4.1 Achieving Energy Autonomy and Improving Grid Resilience

Due to its self-sufficient power generation capabilities, the microgrid configuration diminishes reliance on the primary grid. This self-sufficiency becomes especially advantageous in the event of central grid outages or breakdowns, as it guarantees a consistent electrical supply for vital facilities and operations. Microgrids are engineered to provide superior durability and steadiness compared to more extensive grids. They can function independently or separately from the central system during disruptions; they play a crucial role in preventing further malfunctions and power outages [10].

2.4.2 Opportunities for Demand-Side Management and Energy Trading

The microgrid system enables precise energy use and production management, utilizing up-to-date data. Adaptability is crucial while engaging in power markets to maximize cost-effectiveness. Microgrids can establish a two-way connection with the primary power grid by exchanging energy in both directions. This capability enables the development of trading models that can either sell surplus electricity back to the grid or participate in demand response methods, potentially resulting in the collection of money.

2.4.3 Operation in Island Mode and Economic Advantages

During emergencies or grid breakdowns, the microgrid operates autonomously, supplying electricity to essential loads without relying on the primary system. This feature enhances the reliability of crucial services. By integrating energy storage and efficient load management into the microgrid, it is feasible to reduce energy costs by optimizing the time of energy consumption and capitalizing on energy arbitrage opportunities [11].

2.4.4 Involvement of Local Community and Assistance to the Grid

Microgrids frequently cater to specific local communities, promoting a feeling of energy self-sufficiency and active community involvement. Both residents and businesses have the opportunity to engage actively in energy trading and management decisions. Microgrids can offer supplementary services to the primary grid, such as regulating frequency and controlling voltage. This enhances the entire grid infrastructure, as stated in the research conducted by Mengelkamp et al. (2018) [12].

Integrating a microgrid system into the trading model improves the energy ecosystem's operational efficiency and sustainability, resilience, and adaptability. The system's capacity to equilibrate local generation, storage, and consumption is well-suited to the ever-changing demands of contemporary energy markets, providing advantages to individual users and the broader energy sector.

2.5 Branch and Bound State Space Tree Algorithm

The Branch and Bound state space tree algorithm is a systematic approach used for solving optimization problems by exploring the solution space in a structured manner [13]. It efficiently finds the optimal solution by dividing the problem into smaller subproblems and systematically evaluating them while pruning branches that cannot lead to better solutions than the current best solution.

The algorithm maintains a tree structure where each node represents a subproblem. It starts with an initial node representing the problem and progressively divides it into smaller subproblems (branching), calculating lower and upper bounds for each subproblem. The algorithm then explores the most promising subproblems first (bound), and if the lower bound of a subproblem is greater than the upper bound of the current best solution, that branch is pruned [2].

Here's a simplified equation representing the algorithm:

$$\begin{gathered}\text{Maximize } f(x) \\ \text{Subject to } g(x) \leq C\end{gathered} \tag{2.2}$$

Where:

$\mathbf{f(x)}$ is the objective function to be maximized.

$\mathbf{g(x)}$ is a constraint function that restricts the solution space.

$\mathbf{x}$ is the vector of decision variables.

$\mathbf{C}$ is a threshold value.

The algorithm systematically explores the feasible solutions by dividing the solution space into smaller regions and keeping track of the best solution. This pruning and exploration process continues until the entire solution space is explored and the optimal solution is identified.

In the context of the innovative electricity meter system, the Branch and Bound algorithm could be used to find the most cost-effective paths for energy trading and distribution by exploring various trade-off options while efficiently eliminating suboptimal solutions.

Chapter 3

Related works

As this is a novel electricity trading model but most of our studies related to any partial types of electricity trading or transaction are found on Blockchain based. The Blockchain technology has sparked a wave of research in various domains, including but not limited to human rights and energy systems. So we took all ample size of knowledge from the related Blockchain based works. These diverse studies jointly expand our understanding of the varied implications of blockchain technology. The concept of a "universal human right to electricity" highlights the intricate link between energy access and the fundamental welfare of persons [14]. The disruptive nature of blockchain technology in several industries and its revolutionary effect on venture capital funding and regional development underscores its ability to alter traditional paradigms. When delving into cybersecurity, blockchain technology is pivotal in bolstering data protection and upholding privacy in an increasingly digitized society. In the meantime, comprehensive assessments assist in pinpointing the precise circumstances and occurrences in which blockchain technology may truly showcase its utility, thereby educating and influencing decision-making processes. The examination focuses on the technological domain, explicitly examining the structures of blockchain frameworks like Hyperledger Fabric. It highlights the intricate nature of permission systems. Incorporating IoT technology with smart grids demonstrates blockchain's revolutionary influence in energy distribution and management [14].

Moreover, the previously mentioned studies offer valuable knowledge of the significance of blockchain technology in advancing the distribution of privacy and guaranteeing the safeguarding of personal data by employing cryptographic methods. Applying blockchain technology in the renewable energy sector, exemplified by the "WePower Green Energy Network," showcases its potential to transform market dynamics and operational frameworks. The articles showcased in this collection collectively illustrate the dynamic and comprehensive scope of the blockchain sector, propelling a new age of technical advancement with far-reaching implications in various areas, including economics and security. Refer to Androulaki et al. (2018).

3.1 Enhancing Electricity Access through Technological Innovation

Electricity provision carries substantial significance regarding human rights and global development progress. Löfquist's examination of the "universal human right to electricity" notion explores the complex interplay between energy accessibility and the general well-being of persons [15]. Löfquist examines the relationship between electricity and socio-economic advancement, explicitly focusing on the impact of energy poverty on the fulfillment of human rights. This perspective underscores the importance of electricity as an enabler of several rights, such as education, healthcare, and enhanced living standards. The research emphasizes the significance of policy frameworks that efficiently address disparities in energy accessibility and ensure the capacity of all individuals to exercise their fundamental rights [16]. This study aims to examine the impact of a particular intervention on cognitive development.

Blockchain technology has been implemented in the energy sector to provide efficient and transparent energy management. Albrecht et al. present a thorough case study exploring the complexities of integrating blockchain technology in the energy industry. This study examines the practical application of blockchain technology in enhancing energy systems. Blockchain can tackle various challenges, such as invoicing, grid management, and data transfer, by enhancing transparency, traceability, and security. The case study showcases the capacity of blockchain technology to drive substantial change in the energy sector by fostering trust and accountability among multiple stakeholders. As per the second reference [17].

Prepayment systems have been created to address the challenges related to electricity payment, especially in regions with limited financial infrastructure. The study undertaken by San-lei et al. explores the subject of "Design of prepayment implementation and its data exchange security protection" in the field of Power Metering Automatic systems. This study examines the technological aspects of implementing prepayment systems for electricity usage, aiming to enhance customer convenience and financial stability for energy providers. The research highlights the significance of ensuring secure data sharing to maintain the integrity of these networks, safeguard against fraudulent activities, and provide fair access to electrical resources. As stated in reference [17], it is clear that.

These three publications jointly contribute to the continuing intellectual discussion on energy access and management. Löfquist's analysis of electricity as an inherent right for all individuals emphasizes the necessity of addressing the problem of energy poverty to promote broader socio-economic well-being. The case study conducted by Albrecht et al. showcases the possibility of blockchain technology transforming the energy business by improving transparency and efficiency. The survey undertaken by San-lei et al. examines the implementation of prepayment systems, emphasizing the intricate technological elements involved in improving payment methods while safeguarding data security. These studies provide detailed insights into several aspects of electricity provision, including human rights issues, technology improvements, and operational execution [18].

3.2 Decentralized Distribution and Pioneering Innovation

The amalgamation of technology and industry has led to substantial and profound transformations, primarily demonstrated by the integration of blockchain technology. Friedlmaier, Tumasjan, and Welpe (year) undertook a study to investigate the disruptive potential of blockchain technology across several businesses. This study investigates the consequences of blockchain technology in many areas, including its influence on industry dynamics, venture capital investment, and regional development. This research thoroughly examines the broader consequences of blockchain technology, highlighting its ability to fundamentally change traditional business models and foster the development of new concepts. This underscores the significant impact of blockchain beyond its initial intended use. The user's text is already scholarly and does not necessitate any revision.

Blockchain technology has a wide-ranging impact on various industries, including cybersecurity systems. Karaarslan and Akbas investigate the realm of "Blockchain-based Cyber Security Systems." The study examines utilizing blockchain technology as a foundational structure for enhancing cybersecurity systems. The study emphasizes blockchain technology's capacity to revolutionize security protocols significantly by employing decentralized and tamper-proof techniques. This study emphasizes the importance of solid cybersecurity frameworks in the modern digital age, marked by the prevalence of threats to sensitive information. This text explores the analysis of how blockchain-based systems offer enhanced security measures against cyber threats. Refer to the publication by Ma et al. (2012). The user's text is already scholarly and does not require any revision.

The inception of blockchain technology can be attributed to Nakamoto's seminal publication entitled "Bitcoin: A peer-to-peer electronic cash system." This paper supplies an overview of the underlying concept of blockchain, which enables safe and decentralized digital transactions. Nakamoto's work lays down the fundamental principles for the broader use of blockchain technology. It demonstrates its potential to fundamentally revolutionize financial transactions and build a decentralized framework for exchanging digital assets [19]. The described study is widely recognized as a crucial contribution to the progress of blockchain technology, stimulating more academic research and significant developments in this field. The user's text is already scholarly and does not necessitate any revision.

Collectively, these studies emphasize the wide-ranging impact of blockchain technology on several businesses. Friedlmaier, Tumasjan, and Welpes' survey on blockchain technology's disruptive capabilities emphasizes its ability to revolutionize established industries. Karaarslan and Akbas highlight the importance of blockchain technology in safeguarding sensitive data, namely in cybersecurity. Nakamoto's significant contribution lays the groundwork for the transformative blockchain revolution, highlighting the immense capacity of decentralized and resilient digital systems. The research presented collectively showcases the broader applications of blockchain technology beyond its initial intent. It is already being employed in various domains, providing the potential for enhanced efficiency, transparency, and security [20].

3.3 Architectural Insights and Decision Frameworks

A comprehensive investigation has been carried out on blockchain technology's design, applications, and challenges in light of its increasing popularity. The scientific article written by Cachin, entitled "Architecture of the Hyperledger Blockchain Fabric," provides a comprehensive understanding of the structure and design of the Hyperledger Fabric framework. This research work offers unique insights into the architecture's distributed consensus mechanisms and modular components through a comprehensive structural analysis. The presented contribution is an excellent resource for people seeking a comprehensive understanding of the technology principles underlying Hyperledger Fabric. The user's text is scholarly and does not require any revision [21].

The potential of blockchain technology goes beyond its fundamental technological framework and has significant implications for various industries. Wang et al. thoroughly investigated several aspects related to the subject topic in their scholarly study titled "Blockchain challenges and opportunities: a survey." The current study employed a survey-based methodology to investigate blockchain technology's diverse challenges and prospects comprehensively. The paper thoroughly analyzes the technological environment, covering aspects such as scalability, security considerations, and prospective applications in many industries. The document is a valuable resource for stakeholders who wish to effectively handle the complexities and opportunities of implementing blockchain technology. The user did not give any text for rewriting [22].

Investigating the most advantageous timing and place for deploying blockchain technology is a subject of considerable academic interest. Wust and Gervais critically analyze the findings in their scientific work "The Necessity of Blockchain." The authors present a systematic decision-making approach to assess the need for blockchain technology in a specific use case, comparing it to traditional database options. The study utilizes an analytical framework to assist readers in critically assessing the appropriateness of blockchain technology. It highlights the need to match technological choices with specific requirements and expectations. The user's text is scholarly and does not require any revision [2].

The ongoing investigations into blockchain platforms are crucial in promoting the progress and enhancement of this field. The study by Nasir et al. titled "Performance analysis of Hyperledger fabric platforms" thoroughly evaluates platforms built on the Hyperledger Fabric framework [23]. This study offers valuable insights into the scalability and efficiency of the platform by carefully analyzing characteristics such as transaction throughput and latency. Moreover, Valenta and Sandner's research essay "Comparison of Ethereum, Hyperledger Fabric, and Corda" thoroughly assesses the three blockchain platforms. This study comprehensively evaluates various blockchain platforms, examining their advantages and constraints across multiple dimensions. The research above is crucial in aiding decision-makers in making informed assessments regarding utilizing blockchain technology. The user's text lacks substantive content that can be rephrased in a scholarly fashion. The user's text lacks the necessary depth and complexity to be rephrased in a scholarly fashion. These papers provide a thorough and diverse perspective on blockchain technology. The documents in question contribute to blockchain's progress and real-world application in modern technology environments by understanding its complex structure, examining its difficulties and possibilities, making well-informed choices about its suitability, and assessing its performance [23].

3.4 Authorization Mechanisms for Internet of Things-Enabled Energy Solutions

The progress of blockchain technology has led to the development of platforms that cater to specialized needs, such as permissioned blockchains. The paper by Androulaki et al. presents the Hyperledger Fabric framework, specifically built as a distributed operating system for networks that use permissioned blockchains. The writers offer a thorough elucidation of the design concepts and constituents that constitute the basis of the fabric. This explanation provides essential information on the role of cloth in enabling secure and scalable enterprise blockchain systems. This work is vital to understanding the application of distributed operating systems to meet the needs of permissioned blockchains. The user provided no text for rewriting [24].

Integrating the Internet of Things (IoT) into energy systems has substantial promise for transformation. The essay by Hua, Junguo, and Fantao investigates the relationship between Internet of Things (IoT) technology and smart grids in a paper. The authors explore the capacity of the Internet of Things (IoT) to enhance the effectiveness, surveillance, and administration of energy distribution. This study offers vital insights into the potential of the Internet of Things (IoT) to bring about a substantial revolution in the energy sector. The Internet of Things (IoT) has the potential to enhance energy ecosystems by enabling the sharing of real-time data and optimizing their operations, leading to sustainability and resilience. The user provided no text for rewriting [25].

Safeguarding privacy and securing personal data pose significant obstacles in digital technology. An examination of the potential of blockchain technology to decentralize privacy has been conducted. In their 2015 study, Zyskind, Nathan, and Pentland examined the use of blockchain technology to enhance the security and protection of personal data. The authors' proposed architecture leverages cryptographic techniques and the inherent immutability of blockchain technology to enhance data privacy. This study highlights the growing significance of blockchain technology in tackling current issues regarding data security and personal privacy. The user did not provide any content to revise in a scholarly fashion.

Moreover, the application of blockchain technology has been noted in the field of renewable energy. The white paper "The WePower Green Energy Network" introduces a platform designed to revolutionize the energy industry. The primary objective of the WePower platform is to streamline and make transparent transactions in the renewable energy industry by leveraging blockchain technology. This paper shows a thorough study of the potential influence of blockchain technology on the buying and selling of environmentally friendly energy. It can transform the operations of energy markets completely. This demonstrates the versatile qualities of blockchain technology, highlighting its capacity to go beyond traditional sectors and be helpful in various fields. The user's text lacks substantive content that can be rephrased in a scholarly fashion.

Chapter 4

Proposed Work with Methodology and Performance Study

4.1 Proposed Work

In modern society, consumers' usage of electricity in their homes is experiencing a continuous and increasing rise, mainly due to the widespread adoption and use of electrical and electronic equipment. The growing dependence on these devices has consequently led to a continuously rising need for power [26]. As a result of this increased demand, electricity usage frequently exceeds pre-established threshold levels, resulting in consumers being charged higher tariff rates. As a result, consumers are forced to pay higher financial expenses, even when the amount they consume goes little beyond the limit. In addition, the financial strain is worsened by seasonal fluctuations, such as increased consumption during summer and winter seasons, which need greater monetary spend due to higher tariff tiers. It is crucial to emphasize that these higher tariff tiers involve significantly higher expenditures compared to the previous tiers, which presents a significant problem that requires careful assessment.

Furthermore, the temporal dynamics of electricity consumption, particularly during peak seasons such as summer and winter, contribute to the exacerbation of this financial strain, as the associated higher tariff slabs entail greater expenditure. It is noteworthy that the incremental costs associated with these higher slabs are notably disproportionate to the increased consumption, thereby emerging as a central concern demanding comprehensive attention. In response, this study proposes an innovative electricity trading plan among consumers, characterized by the integration of a billing system within a time series forecasting framework, with a focus on enhancing cost-effectiveness and ensuring the security of the proposed system.

4.1.1 Objectives

The primary objective underpinning the novel trading model introduced in this study is to mitigate the cost associated with energy consumption for consumers, with particular emphasis on achieving this outcome without necessitating a reduction in their overall electricity usage. Additionally, the model seeks to create a revenue-generating avenue for those consumers whose electricity consumption levels are relatively lower compared to their counterparts. The envisaged outcome of this research is to engender benefits that accrue to both high and low-consumption consumers within the electricity market, thereby establishing a more equitable and mutually advantageous arrangement.

This proposed trading model represents a strategic response to the pressing concern of escalating energy costs for consumers, with a specific focus on preserving their existing consumption patterns. By doing so, it seeks to address the issue of the financial burden associated with energy consumption while concurrently providing opportunities for revenue generation, especially for consumers characterized by lower electricity consumption. The envisaged outcome of this research is the creation of a framework that ensures a favorable economic impact for both high and low-consumption consumers, fostering a dynamic that promotes fairness and mutual benefit within the electricity market. The trading information as well as the billing system will be maintained to solve the privacy of user data, billing trust, and security problems of meter reading and measurement. This model has key actors and these are:

- Users/Consumers
- Distributors
- Smart meter system
- Unified billing system

Furthermore, the temporal dynamics of electricity consumption, particularly during peak seasons such as summer and winter, contribute to the exacerbation of this financial strain, as the associated higher tariff slabs entail greater expenditure. It is noteworthy that the incremental costs associated with these higher slabs are notably disproportionate to the increased consumption, thereby emerging as a central concern demanding comprehensive attention. In response, this study proposes an innovative electricity trading plan among consumers, characterized by the integration of a billing system within a time series forecasting framework, with a focus on enhancing cost-effectiveness and ensuring the security of the proposed system.

4.2 Methodology

Electricity consumption, a fundamental aspect of energy utilization, represents the quantum of electrical energy employed by end-users across various sectors. In the context of sustainable energy management and resource optimization, the concept of energy exchange or redistribution, involving the transfer of excess electricity from one user to another, is an emerging paradigm with significant potential. This practice, often referred to as peer-to-peer electricity sharing or decentralized energy sharing, can be instrumental in mitigating grid congestion, enhancing energy resilience, and fostering more efficient resource allocation.

The practice of energy redistribution has emerged as a promising solution to address fluctuations in energy supply and efficiently meet users' energy demands. In such a system, surplus energy generated by one user, typically from renewable sources such as solar panels or wind turbines, can be channeled to other users who may require additional energy at that moment. This form of decentralized energy sharing holds the potential to alleviate grid congestion, reduce energy wastage, and enhance overall energy reliability. To facilitate this aim, we have introduced our strategy to use the surplus energy of any individual to another user [26]. In that way users can participate in energy-sharing networks, thereby contributing to a collective effort in reducing overall energy wastage and environmental impact. For that, we have used both quantitative and forecasting analysis of a long period of energy consumption data of many users. This section will deal with those processes, data collection, preprocessing, and methods.

4.2.1 Data Description

The dataset under examination pertains to the energy consumption patterns of approximately 742 customers. This dataset encompasses a temporal span of approximately three months, systematically recording the daily energy usage of this clientele. It is imperative to note that the dataset has been meticulously sourced from reputable channels directly associated with organizations deeply involved in the field of energy consumption management 4.5.

Customer	**Date**	**Consumption Rate(Unit)**
1113025	05/01/2021	960
1113025	05/05/2021	967
1113023	05/03/2021	1,521
1113023	06/23/2021	1,703
1113008	07/07/2021	937
1113002	07/28/2021	4,038
1112990	07/22/2021	1,469
1077573	05/18/2021	1,198
1077378	06/22/2021	1,400

Table 4.1: Sample dataset of energy consumption

The primary dataset consists of three essential attributes, which include the date parameter, serving as an independent variable in our analysis, customer identification numbers, and the corresponding daily consumption rates. These attributes collectively form the foundation of our research, enabling us to investigate and discern the trends and patterns in energy consumption over the specified time frame.

In addition to the primary dataset, we have also obtained a supplementary dataset, which comprises the comprehensive electricity tariff plan established by a prominent electricity distribution company. This supplementary dataset provides invaluable information regarding the distinct unit prices associated with varying levels of unit consumption exhibited by individual customers. This data aids in understanding the intricate pricing structures and cost implications for electricity consumption based on the specific consumption "slaps" or tiers in which consumers' monthly consumption is categorized. It essentially forms the basis for charging customers in accordance with their respective consumption tiers, facilitating a more nuanced and equitable billing approach 4.5.

Slap	**Lower Unit**	**Upper Unit**	**Unit Price(BDT)**
1	0	75	4.19
2	76	200	5.72
3	201	300	6.00
4	301	400	6.34
5	401	600	9.94
6	6001	1000000	11.46

Table 4.2: Electricity Tariff Plan of an Electricity Distributor Company

4.2.2 Data Preprocessing

In the course of our research, the data pre-processing phase has undergone a comprehensive two-step process. Firstly, we meticulously curated a refined list of eligible buyers and sellers from the entire customer base, leveraging their respective monthly consumption rates within a specific time frame, which, in our study, encompassed the period from day 1 to day 25. To establish eligibility, we set consumption thresholds: sellers were identified based on a consumption limit of up to 300 units, while buyers were defined as those with a consumption exceeding 300 units.

A preliminary data refinement step was essential to facilitate the accurate forecasting of daily power consumption. This involved the removal of select data points deemed potentially detrimental to the forecasting process, thereby ensuring the dataset's reliability and robustness. Besides, the Datetime value of power consumption has been formatted into only date and in a specific sequence so that the forecast model can easily be understood 4.3.

Subsequently, we computed daily unit usage for each eligible customer. This calculation entailed subtracting the previous day's consumption rate from the current day's rate, a crucial step in understanding and predicting power consumption patterns.

Additionally, our dataset included essential information from sellers, such as the number of units they were offering to sell to buyers and the corresponding unit prices. This

Sellers No	Unit to be sold	Price
1113025	97.0	5.94
1113015	51.0	5.87
1077092	24.0	6.21
1077090	6.0	5.82
1112975	40.0	5.90
1077086	50.0	6.12

Table 4.3: Sellers Data Sample

information contributed significantly to the comprehensive analysis of the power consumption ecosystem.

In summary, our research paper details a comprehensive data pre-processing methodology comprising two pivotal phases: the meticulous selection of eligible buyers and sellers based on their monthly consumption profiles, the subsequent prioritization of eligible buyers, the elimination of extraneous data points, the computation of daily unit usage, and the inclusion of key seller-specific data to enable precise forecasting of power consumption over a seven-day forecasting horizon.

4.2.3 Working Strategies

This segment within the methodology chapter will delineate the fundamental framework underpinning the research, incorporating several key components such as the forecasting procedures, the construction of analytical models, the intricate dynamics of energy allocation from sellers to buyers, and the intricacies involved in the identification of buyers and sellers within the context of the research. Furthermore, the section will delve into the prioritization protocols contingent upon the quantum of units involved and the intricate computation processes responsible for ascertaining the prices assigned to the units transacted. Notably, these pricing evaluations will manifest nuanced variations tailored to the individualized tariff structures in place for each respective buyer, underscoring the multifaceted nature of this energy transactional system.

Forecast Model Build

In the endeavor to create a forecasting model for understanding customer power consumption, the research employed the ARIMA model. Before subjecting the customer dataset to this forecasting model, a rigorous pre-processing phase was conducted. This dataset comprises timestamps and corresponding consumption values, and it was meticulously scrutinized. The primary goal was to discern whether the data exhibited features of stationarity, a fundamental requirement for the effective application of time forecasting models, given its direct influence on forecasting model performance. Fig. 4.1 gives an idea of the sample energy consumption data of customers.

Following data visualization, the research undertakes a meticulous decomposition of

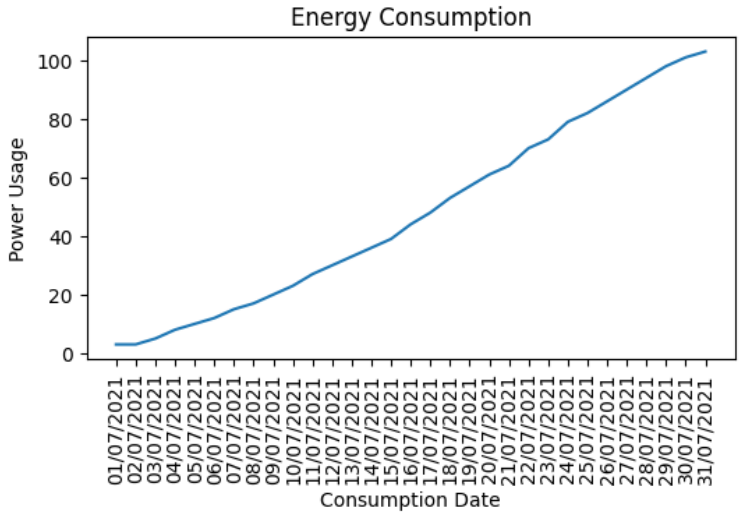

Figure 4.1: Monthly Energy Consumption of a customer

the dataset using an additive approach. This multifaceted operation aims to disentangle the data into its constituent components, including the trend, seasonality, and residual elements.4.2 represent after decomposition graph of a customer.

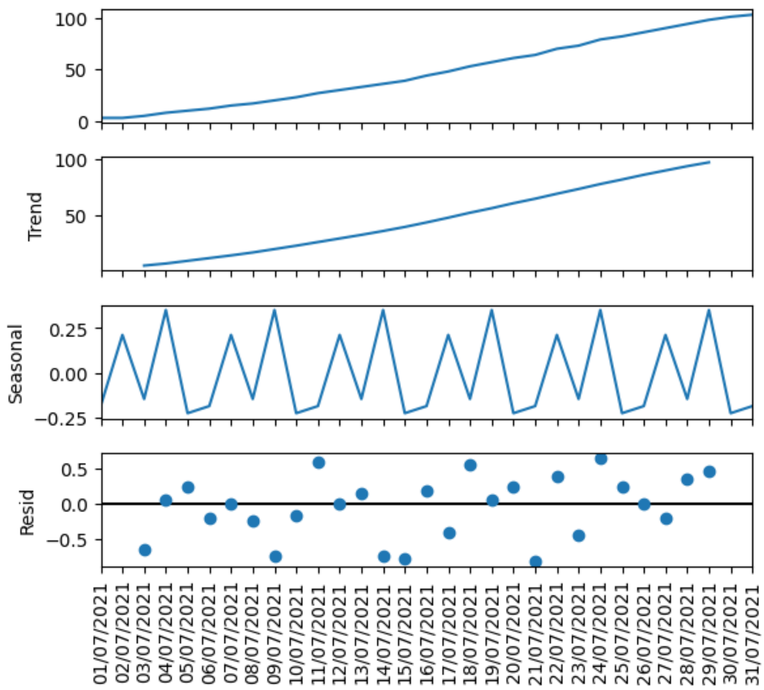

Figure 4.2: Decomposion of sample data to identity trend, seasonality, and residual

Our analysis shows that the examined data displays fluctuations in its overall and seasonal patterns, suggesting that the dataset contains nonstationary properties. Fortunately, the ARIMA model demonstrates its utility in tackling this specific scenario. The "I" (differencing) component of the ARIMA model is essential for transforming nonstationary data into a stationary form. In addition, we have performed the Augmented Dickey-Fuller (ADF) test to choose the stationarity of the client data. The ADF test is widely used statistical test to find out whether a given time series data is stationary or not.

In preparation for the application of forecasting models, the dataset is judiciously divided into distinct training and testing subsets. The training dataset encompasses the initial 25 days of power consumption data, while the testing dataset consists of the following six days. This partitioning is pivotal to facilitating model calibration and validation. The training dataset is employed to build and fine-tune the forecasting model, while the testing dataset serves as an independent subset for evaluating the model's predictive accuracy. This partitioning process ensures that the model can effectively generalize to new data, enhancing its practical utility in forecasting customer power consumption.

The final operational phase entails an iterative approach to select the most appropriate values for the ARIMA model's parameters, represented as p, d, and q. These parameters, which correspond to the order of autoregression, differencing, and moving average, respectively, are pivotal in configuring the ARIMA model optimally. The iterative approach systematically explores various combinations of these parameters to identify the configuration that yields the best-fitting model. This iterative process ensures that the ARIMA model is fine-tuned to maximize forecasting accuracy and minimize errors, thus enhancing its predictive capability. Mostly assigned range for p,d,q includes p in range(0,5) q in range(0,5),d in range(0,2).So, after getting the optimal fine-tuned parameters for ARIMA, we finally applied those parameters to again train the model with our training data. This approach maximizes the efficiency of the model to correctly understand the patterns and complexity of the train data and prepares itself for unknown data to predict. After that, we applied the trained model to predict our test data. ARIMA provides accurate predictions regarding power consumption over the next six days. This modeling operation underpins informed decision-making in energy management and resource allocation.

Through the execution of these meticulously designed research operations, this study aims to provide robust insights into the intricacies of power consumption forecasting. The comprehensive approach, encompassing data visualization, decomposition, stationarity analysis, model training, and iterative parameter optimization, ensures the reliability and accuracy of power consumption forecasts, thereby facilitating well-informed decision-making in the domain of energy management and resource optimization.

4.2.4 Energy Distribution

Seller and Buyers

The foundational step involved the creation of a distinct dataset exclusively dedicated to a subgroup of "sellers" and "buyers" within the customer dataset. This particular classification was achieved through the establishment of an energy consumption threshold, encompassing a range of up to 300 units and more than 300 units. By applying this well-defined threshold, the research systematically identified and isolated entities or individuals exhibiting characteristics indicative of energy sellers within the broader customer dataset.

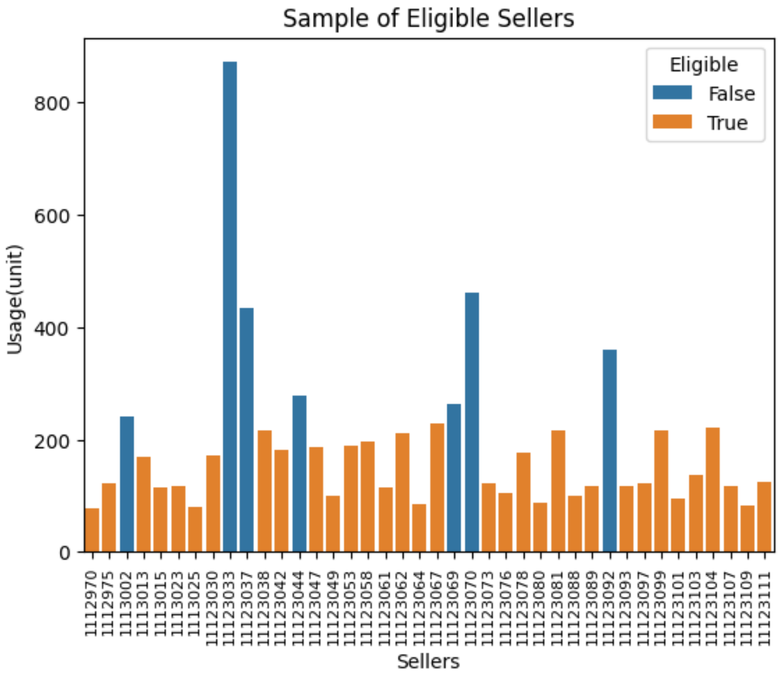

Figure 4.3: Sample of eligible sellers

Within the subgroup of identified sellers, a more intricate categorization was executed, specifically focusing on those whose energy consumption remained below the threshold of 200 units. For this subset of sellers, a comprehensive unit price calculation process was undertaken. The process was meticulously structured, commencing with the subtraction of their monthly predicted energy consumption from the predefined threshold of 200 units. Subsequently, the calculated unit consumption, reflecting the energy consumed within this specific range, was subjected to a precisely designed pricing computation. The computation of unit price per customer energy consumption was meticulously aligned with the corresponding price "slabs" or segmented pricing structures, ensuring that the unit price for this subgroup was determined with a high degree of accuracy.

A parallel pricing calculation process was systematically implemented for another subset of sellers whose energy consumption fell within the range of 200 to 300 units. This particular subgroup exhibited a distinct energy consumption pattern, necessitating a unique pricing approach. Mirroring the previous step, the research initiated the calculation by subtracting the monthly predicted energy consumption from the upper boundary of 300 units. This subtraction operation culminated in the precise delineation of the specific unit consumption within this range. The unit price, thus ascertained, underwent a dedicated pricing computation process that was rigorously aligned with the corresponding price "slabs." This method was executed to ensure that the unit price for sellers within this range was determined with the highest level of precision.

Within the seller categorization, an additional operation was conducted to identify and

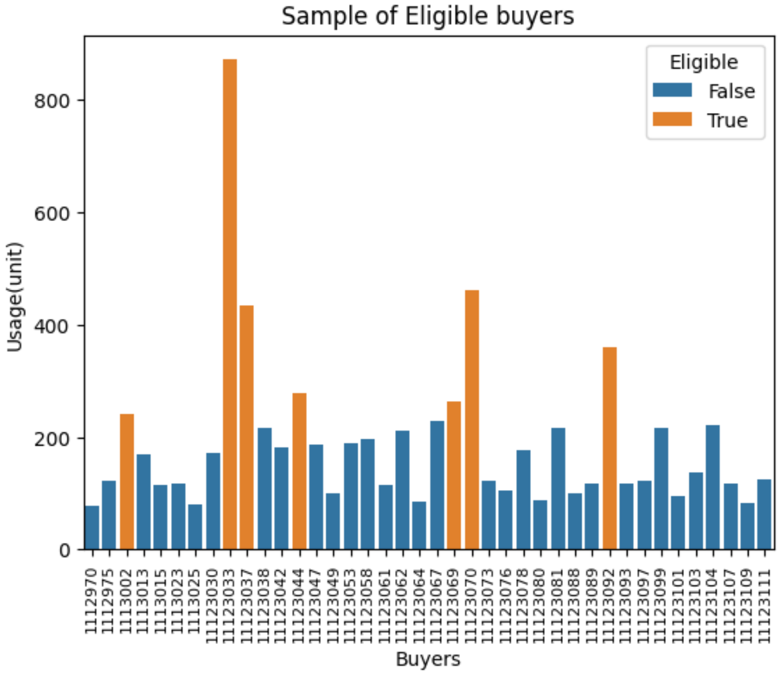

Figure 4.4: Sample of eligible buyers

Buyers No	Usage	Monthly Prediction	Unit Needed
111300	242	315.0	73.0
11123069	264	344.0	80.0
1077132	503	654.0	151.0
1077119	271	353.0	82.0
1077087	462	601.0	139.0
1077134	236	307.0	71.0

Table 4.4: Buyers Data Sample

isolate a unique group known as "buyers." These buyers were identified among the customer dataset based on their energy consumption levels exceeding the minimum threshold of 200 units. This process allowed for the systematic identification of customers with energy consumption that exceeded this threshold, effectively distinguishing them as buyers within the dataset. Table 4.4 shows the sample of buyers.

Buyers Eligibility

In the formulation of the buyer's eligibility with priority list, a systematic approach has been undertaken to allocate priority for the acquisition of power units. This process involves a detailed comparison of each buyer's actual unit usage and monthly predicted power unit consumption against predefined tariff slabs, characterized by both higher and lower consumption limits. The essence of this methodology lies in the nuanced evaluation of buyers' consumption patterns within the delineated tariff slabs.

Specifically, the comparison encompasses an assessment of whether a buyer's unit usage and monthly predicted power unit consumption fall within distinct (next) tariff slabs or share the same slab. If the buyer's consumption metrics place them in the next tariff slabs, this is identified as an eligible situation for the buyers. In such instances, the differentiation in slab placement signifies a higher level of urgency or significance in terms of allocating power units to these particular buyers. The corresponding costs for the remaining needed units of the eligible buyers are calculated based on the predefined tariff plan. The higher the cost of a buyer will be considered more prioritized eligible buyer and so on.

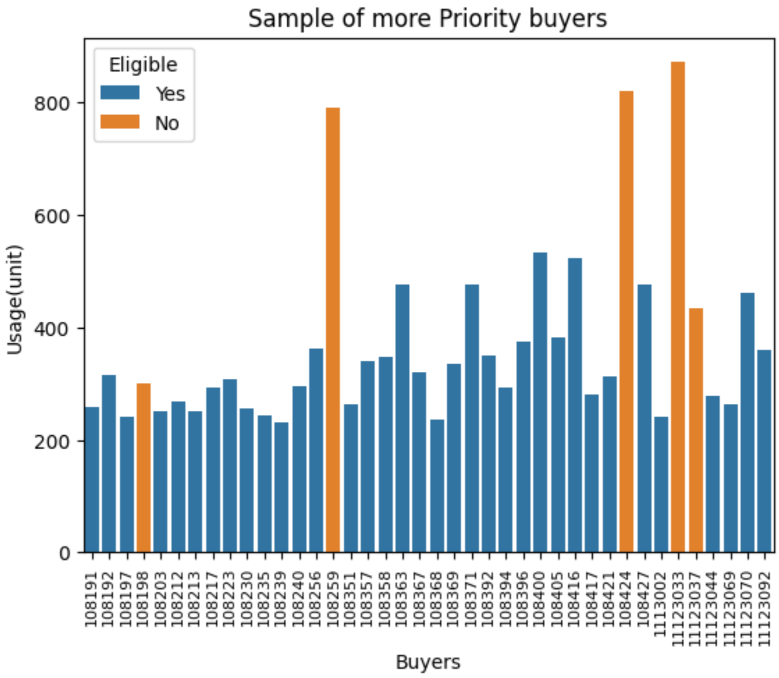

Figure 4.5: Sample of more priority buyers

Conversely, when a buyer's unit usage and monthly predicted power unit range coincide within the same tariff slab, they are categorized as non-eligible buyers. This categorization reflects a situation where the buyer's consumption characteristics do not exhibit significant variations or disparities, leading to a diminished urgency in prioritizing their access to power units 4.5.

This nuanced approach ensures a differentiated and strategic allocation of priority based on the distinct placement of buyers within tariff slabs. By recognizing and leveraging variations in consumption patterns, the priority list is structured to align with the diverse energy needs and usage dynamics of buyers, thereby contributing to a more equitable and informed decision-making process in the realm of power unit distribution.

The potential algorithm is developed to identify both the prioritized eligible buyers and non-eligible buyers. Some certain priority criterion are maintained for the Eligible buyers. The criterion are:

1. A buyer's usage unit has to cross the current slap with respect to the current usage (here 26/05/2021) and the month end predicted usage will be eligible to buy. Here

month end prediction will be incurred using ARIMA time series model.

2. The extra unit needed from the current date (here 26/05/2021) to month end will be find out with the cost. The higher the cost will get more priority.

Algorithm 1 Eligible and non-eligible buyers

Priority(BName, Met_No, Usage, Mon_Prdt, Tariff, N, TS)

```
// BName is a global array containing the names of the buyer's
// Met_No is a global array containing the corresponding meter no. of the buyer's
// Usage is a global array containing the corresponding Unit reading at 26/05/2021
// Mon_Prdt is a global array containing the corresponding monthly usage prediction of
//the buyer's
// Tariff is a global matrix containing the tariff plan
// N is a global variable containing the no. of the buyer
// TS is a global variable containing the no. of tariff slaps
// Current_Usage, Cuslap, Monthly_Usage, Fpslap are the local variables containing the
//current reading, the Current usage slap, Monthly predicted usage and the final
//usage slap respectively of the corresponding buyer
// Eligible, Rucost and Priority are the Global array of the buyer's
// Bnepl is a global matrix containing the info about Buyer's not eligible priority list
// Bepl is a global matrix containing the info about Buyer's eligible priority list
{
    for i = 1 to N
    {
        Current_Usage = Usage[i]
        Monthly_Usage = Mon_Prdt[i]
        UN[i] = Monthly_Usage – Current_Usage //Extra Unit Needed for each buyer at month end
        RU_Cost[i] = Get_Cost(Tariff, Current_Usage, Monthly_Usage, TS)
        Eligible[i] = Get_Eligible(Tariff, Current_Usage, Monthly_Usage, TS)
        K = 1, M=1
        If (Eligible[i] = 'No')
        {
            Bnepl[k][1] = Sl[i]
            Bnepl[k][2] = Met_No[i]
            Bnepl[k][3] = RU_Cost[i]
            K++
        }
        Else // to construct Non Eligible Buyer's Priority matrix
        {
            Bpl[M][1] = Sl[i]
            Bpl[M][2] = Met_No[i]
            Bpl[M][3] = RU_Cost[i]
            M++
        }
        Sort (Bnepl[K][3]) //Any kind of sort based on cost i.e. Bnepl[k][3]
        Sort (Bepl[M][3]) //Any kind of sort based on cost i.e. Bepl[M][3]
    }
}
```

Algorithm 2 Cost calculation of remaining monthly usage sub module

```
Get_Cost(Tariff, Current_Usage, Monthly_Usage, TS)
{
    for j = 1 to TS
    {
        If (Current_Usage ≥ Tariff[j][2]  &  Current_Usage ≤ Tariff[j][3])
            Cuslap = j
        If (Monthly_Usage ≥ Tariff[j][2]  &  Monthly_Usage ≤ Tariff[j][3])
            Fpslap = j
    }
    Cost = (Tariff[Cuslap][3] - Current_Usage) x Tariff[Cuslap][4] +
        (Monthly_Usage - Tariff[Cuslap][3]) x Tariff[Fpslap][4]
    Return Cost
}
```

Algorithm 3 Eligible & Non-Eligible buyer Selection sub module

```
Get_Eligible(Tariff, Current_Usage, Monthly_Usage, TS)
{
    for j = 1 to TS
    {
        If (Current_Usage ≥ Tariff[j][2]  &  Current_Usage ≤ Tariff[j][3])
            Cuslap = j
        If (Monthly_Usage ≥ Tariff[j][2]  &  Monthly_Usage ≤ Tariff[j][3])
            Fpslap = j
    }
    If (Cuslap = Fpslap)
        Return 'No'
    Else
        Return 'Yes'
}
```

Power distribution

In the conclusive phase of the surplus power unit distribution process from sellers to buyers with heightened priority, a meticulously structured series of operations is meticulously implemented. Initially, a comprehensive quantitative assessment is conducted to determine the aggregate available units from sellers designated for sale, juxtaposed with the cumulative power units required by the prioritized buyers. Subsequently, for each eligible prioritized buyer, a detailed evaluation ensues to identify sellers whose sold units either match or are less than the units required by the respective buyer. For these eligible sellers, a precise computation of the buying cost is systematically conducted, representing the intricate financial considerations associated with power unit acquisition.

The Branch and Bound state space tree algorithm is applied to find the sellers list from whom a buyer can buy the required units considering optimal costs. A critical decision-making criterion is then applied, wherein sellers whose buying costs exceed the distributor cost are deliberately excluded. In contrast, sellers with lower costs are strategically considered for unit procurement until reaching a proportionate quota of the total units required by any given buyer. This discerning approach is pivotal to ensuring an economically optimal distribution, with transactions avoiding costs that surpass the distributor's predefined cost threshold. This strategic approach ensures the fulfillment of the primary objective: to provide cost-effective power units to buyers.

Moreover, in scenarios where sellers possess more sold units than the aggregate units sought by buyers, a judicious evaluation is conducted. Units are strategically acquired from such sellers, and the cumulative cost is rigorously monitored. The viability of this approach is contingent on ensuring that the aggregated cost remains below the distributor cost. Only in instances where the cumulative cost aligns with economic prudence, the requisite units are procured from these sellers.

Throughout this iterative process, a meticulous record-keeping system is diligently maintained to track the transactional history of each buyer. This information serves as a foundational basis for subsequent operations, allowing for adaptive decision-making and continual refinement of the surplus power unit distribution strategy. This methodical and strategic approach optimizes the efficiency of the distribution process, ensuring economic prudence and responsiveness to the evolving needs of prioritized buyers within the dynamic energy landscape. Analogous processes are iteratively undertaken for non-eligible priority buyers, ensuring a consistent and methodical approach to surplus power unit distribution.

Let us consider the following electricity tariff plan of an electricity distributor company:

Unit Steps	**Price (BDT)/Unit**
Life line: 00 to 50 Unit	3.75
1st Step: 00 to 75 Unit	4.19
2nd Step: 76 to 200 Unit	5.72
3rd Step: 201 to 300 Unit	6.00
4th Step: 301 to 400 Unit	6.34
5th Step: 401 to 600 Unit	9.94
6th Step: 601 to Above	11.46

Table 4.5: Sample electricity tariff plan

Let's consider the following electricity usage scenario for the month May-21:

Date	Customer Name	Meter No	Usage (Unit)
26/05/2021	Mr. A	0123456	450
	Mr. B	6543210	210
	Mr. C	7894561	125
	Mr. D	1654987	380
	Mr. E	8452654	115
	Mr. F	7418529	202
	Mr. G	1593578	590
	Mr. H	4613798	192

Table 4.6: Electricity usage scenario of 26/05/2021

Now, consider the following Buyer's & Seller's List

Buyer's List			
Sl.	Name	Meter No	Unit Needed
01	Mr. A	0123456	90
02	Mr. D	1654987	75
03	Mr. G	1593578	90
04	Mr. H	4613798	36

Table 4.7: Buyer's List

Seller's List				
Sl.	Name	Meter No	Unit to be sold	Unite Price
01	Mr. B	6543210	45	6.50
02	Mr. C	7894561	45	6.25
03	Mr. E	8452654	60	6.00
04	Mr. F	7418529	50	6.10

Table 4.8: Seller's List

Seller's unit calculation:

Consider the Seller Mr. B:

Day=26, Current Usage=210 Unit, Month end usage prediction by Arima Model: 251 Unit

The seller will consider some more unit for the safety reason with respect to his/her previous usage experience. The App can also help the buyer to calculate the requirement. So, in total the seller will consider 255 Unit for his/her whole month usage.

Sell Unit: Max. Upper level (3rd tariff slap) unit (300) – own usable unite for the month (255) = 45 Unit

Same concept will be applicable for the seller C.

Now, recalling the 1 algorithm to find out the eligible & non-eligible buyers list where eligibility and non-eligibility criteria of the buyers as follow:

Eligible buyer: Monthly predicted usage jumps to next tariff slap

Non-eligible buyer: Monthly predicted usage remains on the same tariff slap

Eligibility with Priority list of the buyer's

Sl.	Buyer's Name	Meter No	Usage (Unit)	Monthly Prediction using Arima Model	Unit Needed	Remaining Unit Cost as per tariff plan	Eligible?
01	Mr. A	0123456	450	540	90	894.60	No
02	Mr. D	1654987	380	455	75	623.80	Yes
03	Mr. G	1593578	590	680	90	1016.20	Yes
04	Mr. H	4613798	192	229	36	213.76	Yes

Table 4.9: Eligibility with Priority list of the buyer's

Eligible Buyer's Priority list			
Sl.	Buyer's Name	Meter No	Remaining Unit Cost
03	Mr. G	1593578	1016.20
02	Mr. D	1654987	623.80
04	Mr. H	4613798	213.76

Table 4.10: Eligible Buyer's Priority list

Non-Eligible Buyer's list			
Sl.	Buyer's Name	Meter No	Remaining Unit Cost
01	Mr. A	0123456	894.60

Table 4.11: Non-Eligible Buyer's list

Optimal Cost Calculation

Let's consider the seller's list 4.8 and consider the list in one dimensional array as follows:

S[ ] = Seller's Name

SU[ ] = Selling Unite of Corresponding Seller

SUP[ ] = Selling Unite Price of Corresponding Seller

So, the seller's list in one dimensional array will be as follows:

Array Name	Array Index			
S[4]	B	C	E	F
SU[4]	45	45	60	50
SUP[4]	6.50	6.25	6	6.10

Table 4.12: Seller's list in Array

After Sorting with respect to seller's minimum unit price offer:

Array Name	Array Index			
S[4]	E	F	C	B
SU[4]	60	50	45	45
SUP[4]	6.00	6.10	6.25	6.50

Table 4.13: Seller's minimum sorted offered price list Array

Now referring the Eligible buyer's priority list 4.10 and Eligibility with priority list of the buyers 4.9, the most eligible prioritized buyer is Mr. G.

For buyer Mr. G

Total Unit needed (TUN) = 90

Maximum cost of the remaining unit (MC) = 1016.20

Now, to find the optimal solution (min. cost for the remaining needed unit) for buyer 'Mr. G', the Branch & Bound state space tree algorithm will be used.

Solution

Step-1: Checking Unit: total selling unit by the seller's > total unit needed by the buyer 'Mr. G'

Here, 60+50+45+45 = 200 > 90 so goto step -2 otherwise exit process

Step-2: Applying Branch & Bound state space tree method

Here, Seller's List (S[ ]), Cost (C), Unit needed (UN), Unit bought (UB), Total Unit bought (TUB), Previous Node (PN), Seller No. (SN), Buying Unit by Buyer (BUB),Optimal Cost Matrix (Info [n][6])

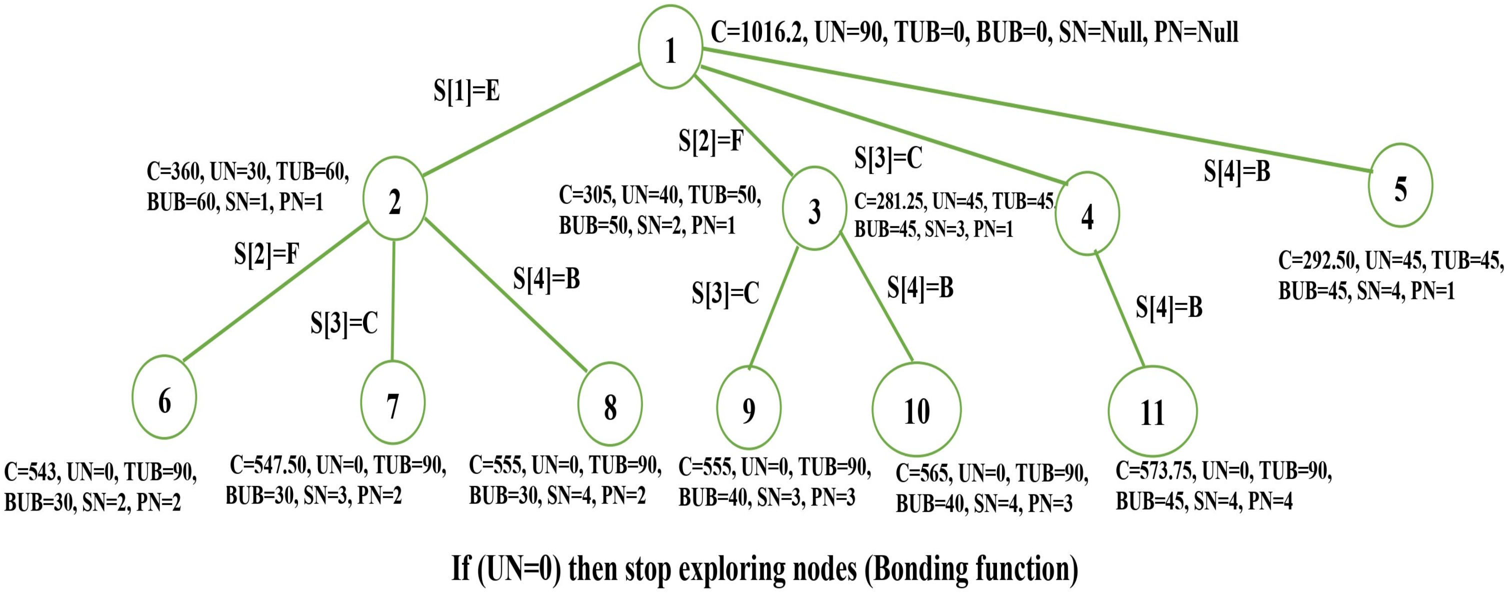

Figure 4.6: Branch & Bound state space tree search to find optimal cost for Buyer Mr. G

Now, no. of nodes, n=11 So, Info[11][6] matrix will be as follows:

Node No.	C	UN	TUB	BUB	SN	PN
1	1016.2	90	0	0	Null	Null
2	360	30	60	60	1	1
3	305	40	50	50	2	1
4	281.25	45	45	45	3	1
5	292.50	45	45	45	4	1
6	543	0	90	30	2	2
7	547.50	0	90	30	3	2
8	555	0	90	30	4	2
9	555	0	90	40	3	3
10	565	0	90	40	4	3
11	573.75	0	90	45	4	4

Table 4.14: Optimal Cost Matrix for the Buyer MR. G

Optimal/Minimum Cost = Min (Info[11][1]) = 543, Node = 6, where Unit needed (UN) = 0

To find the sellers list of optimal cost and Update Selling Unit list i.e. SU[4]

Seller[1] = Info[6][5]= 2 = SN, Info[6][6] = 2 = PN, Info[6][4] = 30 = BUB

Update SU[ ]

SU[SN] = SU[2] = (SU[2] – BUB) = (50 - 30) = 20

Seller[2] = Info[PN][5] = Info[2][5] = 1 = SN, Info[2][6] = 1 =PN, Info[2][4] = 60 =BUB

Update SU[ ]

SU[SN] = SU[1] = (SU [1] – BUB) = (60 - 60) = 0

If (PN = 1) then stop

Seller[2] = {2,1} as this is reverse buying order so reverse the list to get actual buying order from the sellers

Reverse (Seller[2]) = {1,2}

Seller[2] = {1,2} = {E,F}

So, 1st bought from the seller Mr. E and next from Mr. F to get optimal cost.

Now, Update list of the sellers selling unit

SU[4] = {0,20,45,45}

So far described optimal cost calculation process maintains a certain flowchart as well as algorithm which is mentioned bellow:

The flowchart of the whole trading process between buyers and sellers is depicted bellow:

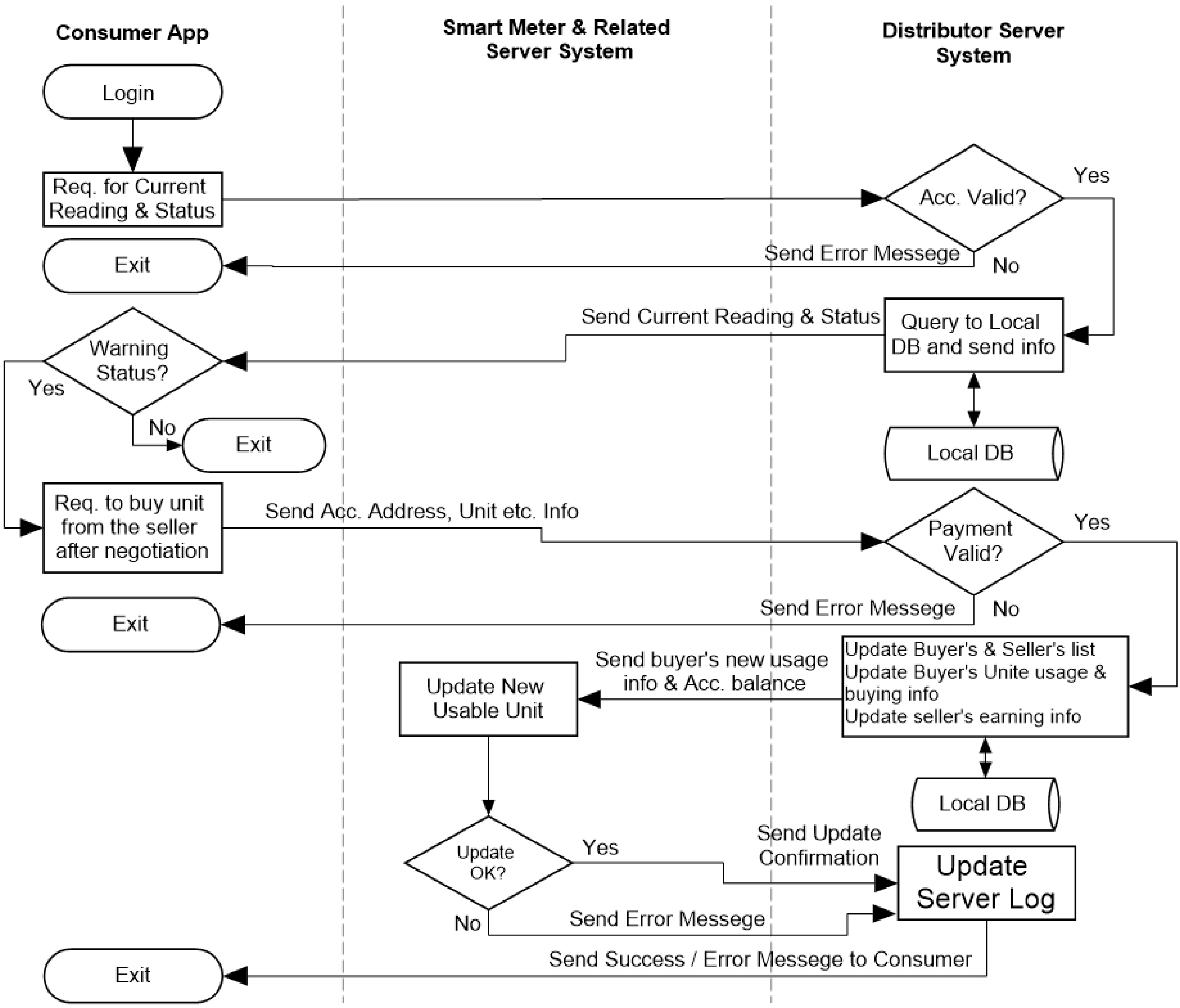

Figure 4.7: Trading flowchart

Algorithm 4 Optimal Cost Calculation

Optimal Cost (N,MC)

```
//Seller[N][4] is a Global Array containing the seller information, where N is the no. of sellers.
//Seller[N][1]= Name, Seller[N][2]= Meter No, Seller[N][3]= Selling Unit, Seller[N][4]= Unit Price
//MC = Maximum cost to buy the remaining unit
//C[N+1] = "Cost" Array
//TUB[N+1] = "Total Unit Bought" array
//BUB[N+1] = "Buying Unit by Buyer" Array
//SMTN[N+1] = "Seller's Meter No." Array
//UN = "Unit Needed" Array
//TUN = "Total Unit Needed" Variable
//UN[N+1] = "Unit Needed" Array
//TSU = "Total Selling Unit" Variable
{
   C[1] = 0, TUB[1] = 0, BUB[1] = 0, SN[1] = Null, TUN = 18, UN [1] = 18,
   TSU = 0 // At the very beginning initialization
   for ( I = 1 to N)
      TSU = TSU + Seller[I][3] //Finding the total selling units by all seller
   If (TSU < TUN)
      Print ('Insufficient Unit') and Exit
   Else
   {
      For (I =2 to N+1)
         C[I] = TUB [I] = BUB [I] = SN [I] = 0 // Initializing the arrays to zero
      For (I =2 to N+1)
      {
         If ((UN[I] = 0) OR (C[I] > MC)) //Checking whether no unit needed or
            Break                          //purchase cost is higher than distributor cost
         Else If (Seller[I][3] = 0) // if the seller has no or zero unit to sell
            UN[I] = UN[I-1] and SKIP this iteration // Unit need will remain same
         Else
         {
             If (Seller[I][3] < UN [I-1]) //if selling unit of this buyer is less than unit needed
            {
               C[I] = C[I-1] + Seller[I-1][3] x Seller[I-1][4] //All selling unit will be bought
               TUB[I] = TUB[I-1] + Seller[I-1][3]
               BUB[I] = Seller[I-1][3]
            }
            Else              //if selling unit of this buyer is greater than unit needed
            {
               C[I] = C[I-1] + UN[I-1] x Seller[I-1][4] //only needed unit will be bought
               TUB[I] = TUB[I-1] + UN[I-1]
               BUB[I] = UN[I-1]
            }
            SMTN[I] = Seller[I-1][2] //Assigning Seller Meter No.
            UN[I] = TUN – TUB[I] //Remaining Unit need calculation
            Seller[I-1][3] = Seller[I-1][3] – BUB[I] //Remaining unit to be sold for the seller
         }
      }
   Return C
   }
```

4.3 Performance Study

This section will comprehensively analyze the implementation of the time series forecasting model and the resulting power distribution outcome. A thorough test of the model's capacity to provide precise predictions is necessary to evaluate the efficacy of the ARIMA in forecasting daily power consumption over one month. This thorough examination entails a wide range of quantitative metrics, visual evaluations, and diagnostic examinations to fully understand the model's skills, constraints, and overall dependability in accurately depicting the intricacies of the time series data. The goal of the analysis is to assess the effectiveness of the ARIMA model in reliably and precisely predicting daily power consumption. The study analyzes the model's capacity to predict outcomes while comprehensively evaluating its diagnostic characteristics reliably. The model's predictions of daily power consumption levels were assessed using a set of quantitative indicators, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Our primary approach for evaluating the performance of the ARIMA model in predicting power consumption for six days has been to use the Root Mean Square Error (RMSE). The statistic measures the average differences between predicted and actual values, thoroughly assessing forecasting precision. The RMSE is calculated using the following equation:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{4.1}$$

Here,

- N is the total number of observations.
- y_i represents the actual observed value at time i.
- $\hat{y}_i$ represents the predicted value at time i.

The process involves calculating the squared differences between observed and predicted values, averaging these squared differences, and then taking the square root of the average. This results in a single metric reflecting the typical forecasting error magnitude. We have calculated multiple RMSE values for different combinations of p,d, and q values to get optimal forecasted output. After that which RMSE comes less in compared to others, we selected those p,d, and q parameters combinations to finally train the model and got an almost accurate prediction of power consumption of multiple customers.

Fig 4.8 shows the diagnostics plots of the ARIMA model. In ARIMA models, the diagnostics function is often used to assess the adequacy of the fitted model by examining diagnostic plots. The diagnostic plots help to identify potential issues with the model assumptions. Our primary concern is to ensure that the residuals of our model are uncorrelated and normally distributed with zero mean. In the histogram (top right), the KDE line almost follows the N(0,1) line (normal distribution with mean 0, standard deviation

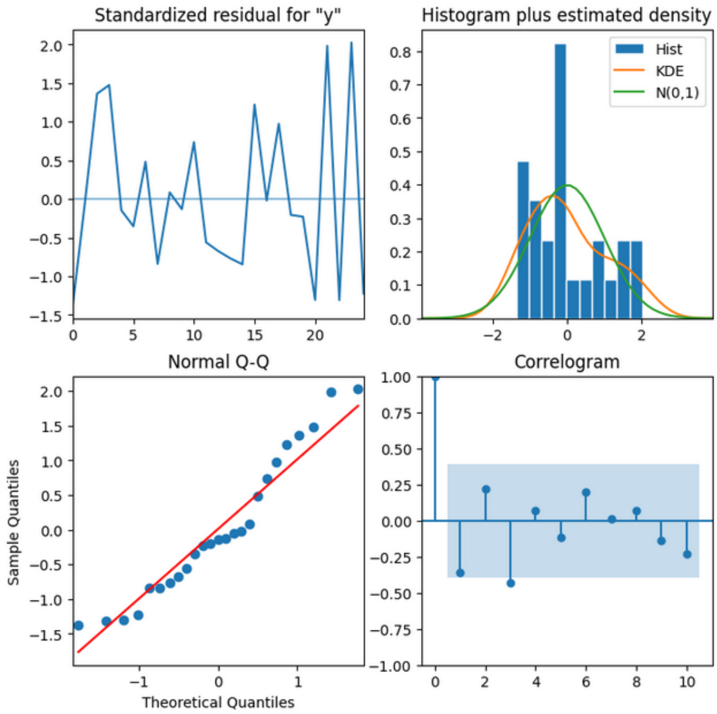

Figure 4.8: Diagnostic Plots of ARIMA Model

1) closely. This is an indication the residuals are normally distributed among the data points. The Standardized Residuals examines if the residuals have a mean of zero and constant variance over time. In our case, it is explicitly visible that, the residuals are maintaining a mean over time through the data points. In the Q-Q-plot the ordered distribution of residuals (blue dots) also follows the linear trend of the samples taken from a standard normal distribution with N(0, 1). The standardized residual plot doesn't display any obvious seasonality. This is confirmed by the autocorrelation plot, which shows that the time series residuals have a low correlation with lagged versions of itself.

Fig 4.9 provides a comprehensive visualization depicting the actual power consumption alongside the forecasted values generated by the ARIMA model over an extended period of six days. The yellow line signifies the observed power consumption units, representing the actual test data from a specific customer. In contrast, the green line illustrates the predictions derived from the ARIMA model, reflecting its ability to anticipate power consumption trends over the designated timeframe.

Within this representation, a notable addition is the inclusion of confidence labels corresponding to the forecasted period. These labels serve to quantify the uncertainty inherent in the model's predictions, offering a delineated range within which future observations are anticipated to lie with a specified confidence level. The width of the confidence interval provides a visual representation of the associated uncertainty, elucidating the extent of potential variations around the forecasted values.

The visual presentation of this figure distinctly highlights the efficacy of the ARIMA model in comprehending the historical patterns of power consumption and subsequently

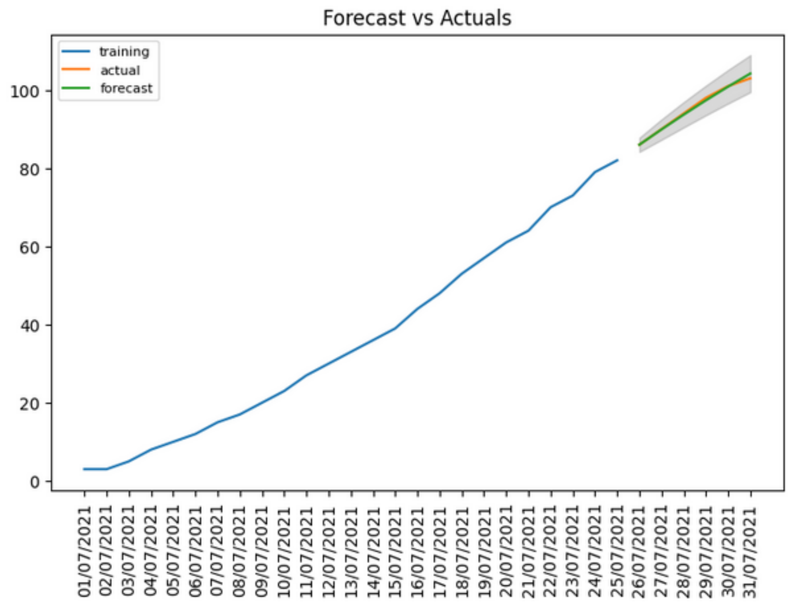

Figure 4.9: Forecast vs actuals

generating forecasts that closely align with the observed test data. The model's capacity to capture and reproduce intricate consumption patterns is evident, substantiating its utility in providing accurate predictions for forthcoming days. This visual assessment contributes valuable insights into the model's performance, emphasizing its reliability in the context of power consumption forecasting.

Table 4.15: Sample of Power Distribution for a Single Buyer

Cost	**Total Bought**	**Bought from Buyer**	**Seller's No.**
75.53	13.0	13.0	108143
81.34	14.0	1.0	1077293
429.94	74.0	60.0	108385
819.21	141.0	67.0	1077471
912.17	157.0	16.0	1077578

Following the prognostication of a customer's daily unit consumption, the anticipated monthly unit consumption serves as a pivotal metric for classifying the customer as either a purchaser or a vendor. Also, the power distribution events unfold based on this categorization. The graphical representation in Table 4.15 encapsulates comprehensive information, encompassing cost details, aggregate purchased units, the provenance of these units, and the residual units after each transaction during a buyer's operational phase. This illustrative depiction elucidates the seamless orchestration of power distribution dynamics among buyers, underscoring the meticulous consideration given to cost minimization in the acquisition of units from sellers.

Notably, the discernible optimization efforts are directed toward identifying the economically advantageous transactions for unit procurement from sellers. Consequently, a delicate equilibrium is maintained, affording equal emphasis on the interests and benefits of both buyers and sellers. The meticulous tracking of these transactions not only enhances the overall transparency of the process but also engenders a heightened level of reliability. In essence, the systematic record-keeping of this intricate transactional framework contributes to the efficacy and dependability of the entire power distribution process, ensuring equitable outcomes for both stakeholders involved.

Table 4.16: Sellers Unit Sold Info

Sellers No	**Buyers No**	**Unit to Sold**	**Sold to Buyer**	**Cost of Sold**
1077552	107979	72.0	72.0	417.60
107936	107979	16.0	16.0	92.80
1077156	107979	86.0	86.0	498.80
1077284	107979	59.0	5.0	29.00
1077284	108091	54.0	54.0	313.20
1077573	108091	32.0	32.0	185.60

Additionally, the corroborative evidence provided by the data presented in Table 4.15 and 4.16 serves to validate the transparent nature of transactions between buyers and sellers within the observed power distribution framework. The meticulous recording and monitoring of these transactions not only fortify the reliability of the process but also act as a safeguard for data privacy considerations. The systematic archival of transactional information not only imparts explicit insights into the intricacies of these interactions but also serves as a foundational measure in ensuring the confidentiality of sensitive data.

This approach to record-keeping not only contributes to the overall transparency of the power distribution dynamics but also establishes a robust framework for safeguarding against potential misuse, malicious intent, or breaches of privacy. By nullifying the possibility of unauthorized access or untoward exploitation, this conscientious data management strategy augments the future resilience of the system, assuring the integrity of the transactional information and fostering a secure environment for all involved parties.

Chapter 5

Conclusion and Future Work

Conclusion

In conclusion, this research has employed a robust methodology, centering around time series forecasting through the ARIMA model, to address the nuanced dynamics of power unit distribution among customers. The utilization of three months' worth of daily power consumption data, sourced from an authorized power distribution entity, facilitated a granular analysis of consumption patterns.

Specifically, a meticulous process was undertaken to filter and categorize customers based on their power consumption behaviors, with a focus on those exhibiting a consistent consumption pattern during the initial 25 days of a given month. The subsequent application of the ARIMA forecasting function enabled the anticipation of power consumption for the remaining Five or six days for the identified subset of eligible customers.

Categorization into sellers and buyers was then executed, predicated upon a predetermined threshold of 200 units. Prioritization of customers further refined the allocation process, establishing a hierarchy for power unit distribution. A pivotal aspect of this allocation strategy involved cost considerations, with the determination of buyer eligibility contingent upon a comparative analysis against tariff slabs and distributor costs.

Noteworthy is the intricate transactional protocol established for buyers necessitating power units spanning multiple slabs. The criterion for such transactions was twofold: equality or greater magnitude of units offered by sellers and a total cost below the distributor's pricing structure. This approach not only optimized cost efficiency for buyers but also fostered equitable transactions within the power distribution network.

The core underpinning of transparency and security was addressed through the individualized tracking of transactions between buyers and sellers. This meticulous record-keeping not only ensures accountability but also mitigates potential issues, aligning with industry best practices for data privacy and transactional integrity.

The suitable algorithms are developed in each part of the whole trading process. This novel electricity trading model can be benefited for both the consumers (buyers & sellers) and the country.

Future Work

In essence, this research contributes to the field by providing a structured framework for optimizing power unit distribution and aligning consumer needs with efficient cost considerations. The outlined methodology offers practical insights that can be extrapolated for real-world application within power distribution systems, with implications for enhancing both economic efficiency and consumer satisfaction. As the energy sector undergoes continued evolution, this research serves as a valuable contribution to the ongoing discourse surrounding optimal power distribution strategies.

The research lays the groundwork for future explorations in optimizing power unit distribution and enhancing consumer satisfaction within evolving energy sectors. Future work could delve into refining and expanding the proposed framework, exploring additional machine learning models for time series forecasting to further improve accuracy. Integration of real-time data and advanced analytics could provide more dynamic and responsive power distribution strategies. Most importantly the Blockchain system can be applied in this trading model where the transactions can be secured. Additionally, investigating the scalability and adaptability of the model to different demographic and geographic contexts would contribute to its broader applicability. Further research could also address the integration of renewable energy sources into the distribution framework, promoting sustainability and resilience. As technology evolves, exploring the potential integration of emerging technologies, such as artificial intelligence and advanced sensors, could offer innovative solutions for even more efficient and secure power distribution systems.

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