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**OPTIMIZING ELECTRICAL POWER
CONSUMPTION IN AL KHUMS, LIBYA,
THROUGH SMART METERS DATA
SIMULATION AND ANALYSIS**

Ans Basher Hussin ALGADI

Master's Thesis

Supervisor

Asst. Prof. Dr. Abdullahi Abdu IBRAHIM

İstanbul, 2025

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The thesis titled OPTIMIZING ELECTRICAL POWER CONSUMPTION IN AL KHUMS, LIBYA, THROUGH SMART METERS DATA SIMULATION AND ANALYSIS prepared by ANS BASHER HUSSIN ALGADI and submitted on 12/05/2025 has been **accepted unanimously** for the degree of Master of Science in Electrical and Computer Engineering.

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I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

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Signature

XXXXXXXXXX

DEDICATION

In the beginning, I thank Allah Almighty for granting me the mental strength, physical health, endurance, divine grace, and ability to accomplish this endeavour. I dedicate this message from the bottom of my heart to my dear father, who has passed away, whose unwavering support was a beacon of inspiration and who often reminded me that my accomplishments are his greatest rewards. I also extend my sincere gratitude to my mother, whose boundless love and constant encouragement have been my pillars of strength throughout this journey, and to my family who spared no effort in supporting me.



PREFACE

First and foremost, I am profoundly grateful to the Almighty Allah, whose infinite grace, strength, and guidance have carried me through every stage of this academic journey. Without His blessings, this thesis would not have been possible.

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ABSTRACT

OPTIMIZING ELECTRICAL POWER CONSUMPTION IN AL KHUMS, LIBYA, THROUGH SMART METERS DATA SIMULATION AND ANALYSIS

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The challenges facing Al Khums in the energy sector are significant, including aging infrastructure, frequent power outages, and heavy reliance on fossil fuels, exacerbated by political unrest and unreliable demand management in the energy sector. Accordingly, this study proposes smart meter technology as a model solution to address these challenges, improve electricity consumption, enhance grid reliability, and support renewable energy integration. This is achieved by simulating and analyzing smart meter data using modern techniques such as Python simulation. The research aims to achieve real-time monitoring capabilities, advanced analytics, and demand management strategies to address energy efficiency shortcomings in Al Khums. The research tools utilized Python-based simulations and data extracted from traditional electronic meters to simulate smart meter functions and then compare performance metrics such as load forecasting accuracy, anomaly detection, and energy loss reduction. The main findings concluded that smart meters enable accurate insights into consumption patterns, reduce technical and non-technical losses through rapid anomaly detection, improve load management, and identify peak demand periods associated with weather and seasonal temperatures. Additionally, smart meters facilitate dynamic

pricing models and demand response programs, empowering consumers to adjust usage and lowering peak demand. The implementation of smart meters in Al Khums is shown to enhance grid stability, reduce carbon emissions, and align with Libya's renewable energy goals. However, challenges such as high initial costs, cybersecurity risks, and public awareness gaps require targeted interventions. Recommendations include pilot programs, regulatory frameworks for data privacy, and infrastructure upgrades to support bidirectional communication. This study contributes a localized framework for smart grid adoption in regions with similar socio-political and infrastructural constraints, emphasizing the role of data-driven solutions in achieving sustainable energy transitions. The results underscore the viability of smart metering as a cornerstone for modernizing Libya's energy sector, offering actionable strategies for policymakers and utilities to improve efficiency, equity, and environmental outcomes.

Keywords: Al Khums, Anomaly Detection, Grid Reliability, Renewable Energy, and Smart Meters.

TABLE OF CONTENTS

	<u>Pages</u>
ABSTRACT	vii
LIST OF FIGURES.....	xiii
ABBREVIATIONS.....	xiv
LIST OF SYMBOLS.....	xvi
1. INTRODUCTION.....	1
1.1 BACKGROUND AND CONTEXT	1
1.1.1 Power Systems and Their Limitations	1
1.1.2 The Emergence of Smart Grids.....	1
1.1.3 The Role of Smart Meters.....	2
1.1.4 Relevance to Al Khums	2
1.2 OVERVIEW OF ELECTRICITY IN AL KHUMS	3
1.3 PROBLEM STATEMENT IN AL KHUMS.....	4
1.4 OBJECTIVE OF THE STUDY	5
1.5 RESEARCH QUESTION.....	6
1.6 SIGNIFICANCE OF THE STUDY	6
1.6.1 Increasing Energy Efficiency.....	6
1.6.2 Support Renewable Energy Initiatives.....	7
1.6.3 Customer Empowerment	7
1.6.4 Economic Consequences	7
1.6.5 Environmental Impact.....	7
1.6.6 Technological Development	7
1.6.7 Deal with Local Challenges	8
2. LITERATURE REVIEW.....	9
2.1 INTRODUCTION	9
2.1.1 Overview of Smart Meters.....	9
2.1.2 Benefits of Smart Meters	9

2.1.3 Role of Smart Meters in Energy Optimization	9
2.2 PREVIOUS RESEARCHES	10
2.3 CASE STUDIES AND PREVIOUS RESEARCHES	14
2.4 DATA SIMULATION IN POWER CONSUMPTION STUDIES	16
2.5 GAPS IN EXISTING LITERATURE	17
2.5.1 Limited Exploration of Intraday Market Dynamics.....	17
2.5.2 Lack of Tail Performance Analysis	17
2.5.3 Exclusion of External Variables	18
2.5.4 Absence of Real-Time Application Testing	18
2.5.5 Exclusive Focus on Short-Term Forecasts	18
3. METHODOLOGY.....	20
3.1 RESEARCH DESIGN AND APPROACH.....	20
3.1.1 Extracting Data from One of the Regular Electronic Meters	20
3.1.2 Descriptive Analytics for Different Parameters.....	26
3.1.2.1 Total active energy	27
3.1.2.2 Total reactive energy.....	27
3.1.2.3 Third total apparent energy	29
3.1.2.4 The voltage.....	31
3.1.2.5 The current	32
3.1.2.6 The frequency.....	32
3.1.2.7 The power factor	33
3.1.2.8 The demand.....	34
3.2 SIMULATING THE SAME DATA FOR THE SAME METER	34
3.2.1 Smart Meter Data Analytics.....	39
3.2.1.1 Load analysis and forecasting	40
3.2.1.2 Energy management systems	40
3.2.1.3 Anomaly detection and fault diagnosis	40
3.2.1.4 Clustering and classification	41

3.3 COMPARING THE RESULTS	56
4. CONCLUSION AND RECOMMENDATIONS	58
4.1 SUMMARY OF FINDINGS	58
4.2 CONTRIBUTIONS TO KNOWLEDGE	58
4.3 RECOMMENDATIONS FOR PRACTICAL IMPLEMENTATION	58
4.4 LIMITATIONS AND FUTURE RESEARCH.....	59
4.5 FUTURE RESEARCH SHOULD CONSIDER.....	59
REFERENCES	60
APPENDIX A.....	66
APPENDIX B.....	73

LIST OF TABLES

	<u>Pages</u>
Table 3.1: Shows the Total Active Energy.....	20
Table 3.2: Shows the Total Reactive Energy	21
Table 3.3: Shows the Total Apparent Energy.....	22
Table 3.4: Shows the Voltage.....	23
Table 3.5: Shows the Current	24
Table 3.6: Shows the Frequency	24
Table 3.7: Shows the Power Factor	25
Table 3.8: Shows the Demand.....	26
Table 3.9: Shows the Reactive Energy in Power Quarters.....	28
Table 3.10: Shows the Instantaneous Apparent Power	30
Table 3.11: Shows the Instantaneous Active Energy	41
Table 3.12: Comparing the Results	56

LIST OF FIGURES

	<u>Pages</u>
Figure 3.1: Shows the Simulating Data from Smart Meter Clarifying Total Active Energy	34
Figure 3.2: Shows the Simulating Data from Smart Meter Clarifying Total Reactive Energy.	35
Figure 3.3: Shows the Simulating Data from Smart Meter Clarifying Total Apparent Energy	36
Figure 3.4: Shows the Simulating Data from Smart Meter Clarifying Voltage I.....	37
Figure 3.5: Shows the Simulating Data from Smart Meter Clarifying Voltage II	37
Figure 3.6: Shows the Simulating Data from Smart Meter Clarifying Current	38
Figure 3.7: Shows the Simulating Data from Smart Meter Clarifying Frequency.....	38
Figure 3.8: Shows the Applications of Data Analytics and Techniques	40
Figure 3.9: Shows the Time Interval 15 Min	43
Figure 3.10: Shows Detecting Non-Technical Losses.....	44
Figure 3.11: Shows the Load Forecasting Categories	46
Figure 3.12: Shows the Different Methods Used for Load Forecasting.....	50
Figure 3.13: Demand Side Management Techniques.....	53

ABBREVIATIONS

ABM	:	About Based Modelling
ACO	:	Ant Colony Optimization
AI	:	Artificial Intelligence
ANN	:	Artificial Neural Network
ANNs	:	Artificial Neural Networks
ARIMA	:	Integrated Moving Average
ARMA	:	Autoregressive Moving Average
CNN	:	Convolutional Neural Network
CP	:	Convex programming
CV	:	Coefficient of Variation
DER	:	Distributed Energy Resources
DSM	:	Demand Side Management
ELM	:	Extreme Learning Machine
EMD	:	Empirical Mode Decomposition
GA	:	Genetic Algorithm
GECOL	:	General Electricity Company of Libya
GRAND	:	Green Radio Access Network Design
ICT	:	Information and Communication Technologies
IoT	:	Internet of Things
KPIs	:	Key Performance Indicators

LSTM	:	Long Short-Term Memory
MA	:	Moving Average
MAE	:	Mean Absolute Error
MAPE	:	Mean Absolute Percentage Error
ML	:	Machine Learning
MSE	:	Mean Square Error
MTLF	:	Medium-term Load Forecasting
PEC	:	Public Electricity Company
PSO	:	Particle Swarm Optimization
RMSE	:	Root Mean Square Error
RNN	:	Recurrent Neural Network
RRSE	:	Root Relative Squared Error
SGO	:	Shell Game Optimization
SMs	:	Smart Meters
SVM	:	Support Vector Machine
THD	:	Total Harmonic Distortion
TOU	:	Time-of Use
VAH	:	Volt Ampere Hour
VARH	:	Volt Ampere Reactive Hour
VM	:	Vector Machines
VSTLF	:	Very Short-term Load Forecasting

LIST OF SYMBOLS

$\wedge$: The Power of

Σ : Sum

C : Current

V : Volt

W : Watt

P : Active Power

Q : Reactive Power

S : Apparent Power

θ : Phase Angel

1. INTRODUCTION

1.1 BACKGROUND AND CONTEXT

Electricity is the backbone of modern society, powering homes, industries, and essential services. However, traditional power systems face significant challenges in meeting growing energy demands, particularly in regions like Al Khums. These challenges include inefficiencies in energy distribution, frequent outages, and difficulty in integrating renewable energy sources. The transition to smart grid technologies, with smart meters as a core element, represents a promising solution for improving electricity consumption and addressing these constraints.

1.1.1 Power Systems and Their Limitations

All mechanisms of conventional energy systems revolve around centralized electricity generation. Power is produced in large-scale plants and transported over long distances to consumers. Despite the efficiency and effectiveness of these mechanisms for decades, the system itself suffers from fundamental problems, such as energy losses during transmission, high infrastructure costs, and an inability to accommodate rapid changes in demand. These problems are particularly acute in areas with aging infrastructure, such as Al Khums. Frequent outages, voltage drops, and line congestion are common, leaving communities with a persistent problem of unreliable power when it is most needed [2]. However, the increasing reliance on renewable energy sources, such as solar and wind power, despite their environmental benefits, traditional grids struggle to manage them. As energy demand increases, it becomes clear that traditional systems are ill-equipped to support sustainable and efficient energy distribution [3].

1.1.2 The Emergence of Smart Grids

Smart grids represent a major advancement in traditional energy systems. They combine advanced information and communications technologies (ICT) with traditional grid infrastructure to create a smart, bidirectional system between energy providers and consumers. Whereas the unidirectional flow of energy in traditional grids did not allow for monitoring and control, smart grids enable real-time, dynamic monitoring and control,

allowing for optimal energy distribution and enhanced reliability [1] [3]. The most important feature of smart grids is their ability to seamlessly combine renewable energy sources. By balancing power generation between solar and wind energy systems with grid demand, smart grids ensure stability and efficiency, even with decentralized power generation. This integration not only reduces dependence on fossil fuels, but also aligns with global sustainability goals [3].

1.1.3 The Role of Smart Meters

Smart meters are the cornerstone of smart grids. These advanced devices provide accurate, real-time data on electricity usage, helping to bridge the information gap between utility companies and consumers. Their ability includes:

- a. Enhanced Monitoring and Data Collection: Smart meters enable utilities to track energy usage patterns across the grid, facilitating better forecasting and load management. [1], [2].
- b. Demand-Side Management: Real-time feedback empowers consumers to adjust their energy usage, reducing consumption during peak times and participating in demand-response programs. [1], [2].
- c. Combining renewable energy sources: Smart meters measure the consumption and contribution of renewable energy resources such as rooftop solar panels. [1], [2].
- d. Increased billing accuracy: Human error is eliminated with automated readings, dynamic pricing models are improved, and energy consumption conservation. [1], [2].
- e. Faster fault detection and repair it: Real-time identification of outages allows for rapid detection of faults and quality issues in specific locations. Smart meters perform this role with high reliability, accelerating response and repair. [1], [2].

1.1.4 Relevance to Al Khums

The energy sector in Al Khums city in Libya faces unique challenges, including aging infrastructure, high population demand, and reliance on fossil fuels. Smart grid technologies are a lifeline for such challenges, especially since smart meters represent a path to modernization and improvement, enabling them to address inefficiencies in energy use, reduce energy losses, and improve the reliability of electricity distribution. The challenges

of traditional energy systems require a shift toward smarter energy solutions. Smart grid technologies, with smart meters at their core, offer a transformative approach to improving energy consumption in Al Khums. By addressing inefficiencies, enabling the integration of renewable energy, and empowering consumers, these innovations pave the way for a sustainable and reliable energy future. Furthermore, the integration of renewable energy sources such as solar—an abundant resource in Libya—in smart grids supports the region's transition to a more sustainable energy future [2], [3]. The implementation of smart meters in Al Khums can keep pace with global trends toward energy digitization, leveraging advanced monitoring, analytics, and automation, enabling the city to lay the foundation for efficient, resilient, and sustainable energy management. This transformation is not only essential to meeting immediate energy demand but also to ensuring long-term economic and environmental benefits [3]. This study draws on the fundamental principles of energy systems and the transformative potential of the smart grid to propose practical solutions for improving energy use in Al Khums. The challenges facing traditional power systems require a shift towards smarter energy solutions. Smart grid technologies, with smart meters as a key component, represent a transformative approach to improving energy consumption in the city of Al Khums. By addressing deficiencies, enabling the integration of renewable energy sources, and granting consumers a more active role, these innovations pave the way for a sustainable and reliable energy future. This study builds on the fundamental principles of energy systems and the transformative potentials of smart grids to provide practical solutions for energy enhancement in the city of Al Khums.

1.2 OVERVIEW OF ELECTRICITY IN AL KHUMS

Outdated infrastructure, rising demand, and ongoing political instability are among the most significant factors impacting the energy sector in Al Khums and across Libya. These challenges have been the direct impact of years of conflict and severe underinvestment in the national electricity grid, resulting in frequent power outages and disruption to daily life and economic activities, especially in areas such as Al Khums. Fossil fuels are the lifeblood of Libya's electricity sector, which is heavily relied upon. The General Electricity Company of Libya (GECOL) operates approximately 20 conventional power plants generating approximately 8,051 megawatts (MW). Actual production is often lower due to equipment failures, inefficiencies, and lack of maintenance. In the summer, peak power demand can

reach 7,500 MW, while generation capacity often remains around 6,320 MW [4], [5]. Al Khums, a coastal city with high demand for air conditioning during the hot months, is severely affected by these energy-related problems. Local power generation facilities such as steam and gas turbines with a total capacity of approximately 960 MW often struggle to operate continuously due to mechanical problems. The cost of this reliance on traditional fuels is high operating costs and a significant contributor to Libya's carbon dioxide emissions [5], [8]. These grid constraints, exacerbated by fuel shortages and an aging distribution network, result in widespread load shedding, ranging from one to twelve hours per day in some areas [8], [11], [35]. The heavy dependence on fossil fuels—around 63% of generation is from natural gas and 37% from oil—means the system is costly and environmentally damaging. Despite these drawbacks, renewable energy development remains limited, although studies show Libya has strong potential for solar and wind energy. Libya's high solar irradiance, particularly in the southern regions, could support small-scale solar installations and mini-grids, reducing dependence on fossil fuels and improving grid reliability [9], [10]. Efforts to address these challenges include the government's launch of renewable energy exploration initiatives and infrastructure investments. However, political instability and funding constraints are hampering progress. International partnerships to modernize the electricity grid have been pursued, but implementation has been slowed by safety and logistical issues. To ensure sustainable and reliable energy, Libya will require significant investments in modern infrastructure, renewable energy development, and energy efficiency initiatives [6], [7], [12].

1.3 PROBLEM STATEMENT IN AL KHUMS

The energy consumption problem in Al Khums is one of the broader challenges facing the national energy sector. For example, the GECOL, which manages the country's electricity infrastructure, suffers from an outdated network that cannot meet the growing demand. Like many other regions, Al Khums experiences frequent power outages and load shedding, severely impacting daily life and economic activity. A significant issue is that Libya's energy infrastructure is outdated and requires urgent maintenance and development to meet current consumption needs, but it lacks the necessary investment and resources to do so [4], [5], [10]. Electricity generation in Libya is highly dependent on fossil fuels, with 63% of Libya's energy coming from natural gas and the remaining 37% from oil. However, operational

inefficiencies mean that the GECOL's actual available capacity is often far below its rated capacity. During peak summer demand, which can reach around 7,500 MW, the grid struggles to supply even 6,320 MW, resulting in routine outages and forced load shedding across all regions, including Al Khums [4], [5]. Political instability and economic challenges since 2011 have hampered both the maintenance of existing infrastructure and the development of new projects, such as renewable energy initiatives. The conflict has damaged infrastructure and led to the migration of skilled engineers and technicians, exacerbating the Public Electricity Company's (PEC) crisis and its challenges in meeting short- and long-term electricity needs [6], [11], [35]. Residential and agricultural sectors in areas such as Al Khums experience high energy demand due to air conditioning needs during hot summers. Low electricity tariffs and, in some cases, unmetered connections contribute to overconsumption and inefficiencies. Studies from areas similar to Al Khums show that unregulated air conditioning is common, exacerbating the supply-demand imbalance without addressing the root causes [5], [11], [35]. Additionally, reliance on diesel generators as a backup option is expensive and environmentally unsustainable [11], [35], [12]. In conclusion, the energy consumption crisis in Al Khums and across Libya is centered on aging infrastructure, limited generation capacity, and the challenges posed by political instability. Insufficient investment and limited integration of renewable energy options are factors that leave Libya dependent on a fragile and unsustainable energy system that fails to meet the needs of the population. Consequently, areas like Al Khums are vulnerable to frequent power outages.

1.4 OBJECTIVE OF THE STUDY

The study conducts with the aim of improving electricity and energy efficiency in Al Khums, by using smart metering technology to increase energy efficiency and reduce consumption. This required the use of smart meters to monitor electricity consumption in real time, allowing for greater efficiency. Monitoring, analysis, management, and the provision of accurate, timely data on efficient usage help improve load management, reduce peak demand, reduce overall energy consumption, reduce carbon emissions, and contribute to a more sustainable and reliable electricity system in Al Khums.

1.5 RESEARCH QUESTION

This study seeks to address a number of important questions to understand and improve energy consumption in Al Khums. By analysing these questions, we can identify which products use the most energy, determine how smart meters can help alleviate problems, and determine the most efficient data solutions for energy consumption work well though.

What are the main factors affecting electricity and electricity consumption in Al Khums?

Al Khums faces unique challenges due to multiple factors influencing capacity management. These include rapid population growth, increased industrial activities and increased seasonal demand during the warmer months when air conditioning is used more. Another factor is the age of exposure and how now electrical systems are inefficient, contributing to high energy losses and limiting the ability to monitor efficiency.

How can smart meters reduce unnecessary consumption?

Smart meters are a powerful tool for reducing energy losses by providing real-time electricity consumption information. They help customers and suppliers understand exactly when and how much electricity is used, so they can adjust usage patterns during peak periods and reduce costs charged on usage. It is not necessary for example to alert consumers to high energy consumption to help them make more rational decisions, such as increased workload. Because energy services change during peak hours, electricity providers can also use smart meter data to balance loads on the network, preventing overuse and reduce operating costs.

1.6 SIGNIFICANCE OF THE STUDY

1.6.1 Increasing Energy Efficiency

The integration of smart meters is essential for increasing energy efficiency in the city of Al Khums. They provide accurate monitoring of consumption, help reduce waste, and improve the management of electrical loads. Smart meters provide accurate time information about energy consumption, empowering consumers and suppliers to identify and address inefficiencies. This ability to reduce overall energy consumption and better meet demand is critical, especially in a region facing energy supply challenges.

1.6.2 Support Renewable Energy Initiatives

The title of the Libyan National Policy on Renewable Energy and Energy Efficiency emphasizes the importance of improving energy efficiency to drive the transition to complementary renewable energy this system by means of smart meters capable of promoting solar, wind and other renewable energy sources, effectively integrated and segregated around.

1.6.3 Customer Empowerment

Smart meters enable customers by providing them with accurate information about their energy consumption. This transparency encourages behavioural changes, which can lead to reduced resource consumption and cost savings. With real-time data, consumers can make more informed decisions about their energy usage, contributing to the sustainability of communities.

1.6.4 Economic Consequences

Improving electricity efficiency through smart meters can bring significant economic benefits for both consumers and utility companies. The total cost of providing electricity can be reduced by reducing waste and improving efficiency of use. In addition, the ease of payment and the ability to pay via smart meters reduce the likelihood of customers experiencing unexpected fees, providing them with greater financial flexibility.

1.6.5 Environmental Impact

The environmental impact of electricity efficiency is profound and of great importance. By reducing public energy consumption and facilitating the adoption of renewables, smart meters contribute to reducing greenhouse gas emissions. This is in line with international efforts to combat climate change and supports a sustainable future for Libya.

1.6.6 Technological Development

The topic also highlights the importance of technological advances in energy management. The adoption of smart meters represents a shift towards more advanced technologies in the management of electrical grids, capable of adapting to changing demand and integrating

with emerging technologies such as artificial intelligence and the Internet of Things. This makes Libya a country with a futuristic vision in the field of energy consumption.

1.6.7 Deal with Local Challenges

Al Khums faces unique challenges related to electricity supply and demand management. The findings of this thesis can provide local solutions according to the specific needs of the community, ultimately improving service reliability and quality. In this research not only addresses important issues related to energy and electricity consumption in Al Khums but also contributes to a broader discussion about growth, economic development and technological innovation is also in the growing energy situation of Libya.



2. LITERATURE REVIEW

2.1 INTRODUCTION

2.1.1 Overview of Smart Meters

Smart meters are advanced units that enable two-way communication between power consumers and tool suppliers. Unlike traditional meters, which require manual readings, real-time data on smart meters provide power consumption, which allows automated monitoring, remote reading and increasing energy management [13]. These meters play an important role in modern energy systems, which contributes to web stability, efficient energy use and improved demand response strategies.

2.1.2 Benefits of Smart Meters

Smart meters provide many advantages on traditional measurement systems. One of the main benefits is his ability to provide real-time consumption data, which helps both consumers and tools optimize energy use [18]. Consumers can monitor their power use patterns and adjust consumption to reduce costs, while the tool supplier can detect electric power outages, prevent energy protection and use time-based price mechanisms [15]. Add to that, smart meters contribute to energy savings by supporting demand-side management (DSM) programs. These programs encourage consumers to convert their energy consumption into off-peak hours, reducing pressure on electricity grids and reducing energy losses [20]. Smart meters also contribute to environmental stability by reducing total energy consumption and reducing carbon emissions [19].

2.1.3 Role of Smart Meters in Energy Optimization

Improving energy efficiency through smart meters involves utilizing real-time data analysis and automation mechanisms to increase the efficiency of energy use. Smart meters allow the application of dynamic pricing models, such as time-of-use (TOU) rates and peak pricing, which encourage consumers to use electricity more efficiently [14]. This helps reduce pressure during peak periods and achieve a more balanced distribution of loads on the electricity grid. Furthermore, smart meters facilitate the integration of renewable energy sources into the grid by providing accurate data on energy production and consumption. This

integration supports the development of smart grids, which is essential for adapting to modern energy requirements division and reduce electricity loss [17]. For Al Khums, the implementation of smart meters can help alleviate the problem of power shortages, improve grid reliability and increase overall energy efficiency. Through the use of simulations and data analysis, tools can predict consumption patterns, identify deficiencies, and use targeted interventions to adapt to energy consumption. The use of machine learning algorithms and large data analysis increases the ability to manage and supply power requirements [16].

2.2 PREVIOUS RESEARCHES

[21] The paper provides a comprehensive overview of how optimization, simulation, and data analysis are integral to the effective design and operation of microgrids, while [22] the paper effectively covers optimization, simulation, and data analysis, demonstrating their interconnections in the context of energy management. In [39] the paper provides a comprehensive look at how optimization, simulation, and data analysis are applied in the context of sustainable smart energy systems. And [40] the paper indeed addresses optimization, simulation, and data analysis as critical components in enhancing the AMI architecture for smart grids. In [41] the paper discusses optimization, simulation, and data analysis in the context of industrial energy conservation and efficiency optimization. While [42] the paper primarily focuses on the regulatory and technological aspects of smart-metering networks, it also incorporates elements of optimization, simulation, and data analysis as part of its broader discussion. In [43] the paper focuses on optimization, simulation, and data analysis in the context of power consumption scheduling for smart homes. In [23] the paper does focus on optimization, simulation, and data analysis within the context of smart meter data analytics. In [44] the paper indeed focuses on optimization, simulation, and data analysis within the context of power consumption in wireless access networks. And in [45] the paper indeed focuses on optimization, simulation, and data analysis as integral parts of its approach to energy management in smart homes. [36] In this paper argued that smart metering is an important research topic due to the problems of electromechanical metering and its energy and time consumption. Current methods focus on data processing rather than efficiency optimization. Predicting electricity consumption is crucial for optimizing smart grids, as it helps in resource planning and balancing supply and demand. Smart metering provides users with an effective understanding of their energy

consumption, helping them reduce costs. The author presented an energy consumption analysis model using the smart metering data model (ECA-SMD), which includes three main processes: data processing, feature extraction, classification, and parameter optimization. The model relies on an extreme learning machine (ELM) to classify data, and a shell game optimization (SGO) algorithm is used to fine-tune the ELM parameters and improve its efficiency. The model's effectiveness was verified using smart metering data, showing the highest accuracy of 65.917% and the lowest mean square error (MSE) of 0.096. The model includes data processing, feature extraction, prediction using ELM, and parameter optimization using SGO.

Optimization: [21] The paper addresses the complexity of microgrid sizing, which involves defining design criteria and objectives to formulate a multi-objective optimization problem. This is essential for determining the best configuration based on energy potential and local demand. [22] The paper presents a mathematical model aimed at optimizing residential energy consumption scheduling. It focuses on minimizing electricity costs and waiting times, which is crucial for effective energy management. [39] The paper highlights various optimization methods used in energy efficiency, including simulation-based optimization, surrogate-based optimization, and different approaches like gradient-based and meta-heuristic methods. [40] The paper discusses the main issues belong optimization for different AMI architectures, highlighted the performance metrics. A genetic-based algorithm is employed to reduce these metrics for the proposed hybrid AMI architecture. [41] The paper reaffirms the importance of optimizing energy management systems. It says that the system model mixes user comfort and preferences, allowing for demand-side management that increases the utilization and decreases electrical bills. [42] The study discusses the optimization of energy generation and distribution among advanced communication networks that need for smart grids, which is the most important thing for monitoring and enhancing efficiency in energy usage. [43] The study discusses the optimization as a crucial for both local storage facilities and utility company demands by using a bi-level quadratic optimization approach to make control about the power consumption levels and reduce costs. [23] The researches address the need for optimization techniques in load forecasting and management, that are necessary for improving the efficiency of energy consumption and grid operations. It makes sure that the importance of algorithms can enhance energy usage dependence on smart meter data. [44] The study addresses the GRAND as a tool of wireless

networks to optimize power consumption. As it dependence on a genetic algorithm to improve energy efficiency during this wireless network. [45]. This paper presents a CP framework for energy consumption in smart homes, that optimizes the scheduling of different household appliances to reduce electricity costs and enhance user satisfaction. [34] The paper addresses the optimization of energy forecasting depending on smart metering to distribution networks. The authors propose a frequency feature-based method to analyze time-series data from smart meters. This approach enhances energy demand estimation, improving power flow management and minimizing energy acquisition costs. The method uses Fourier series decomposition and optimization models to achieve accurate forecasting. A key contribution is a mathematical cost function that optimally adjusts correction coefficients for energy contour estimation.

Simulation: [21] Various commercial software tools for microgrid modelling and simulation are mentioned, such as MDT, DER_CAM, and HOMER. These tools help analyse the behaviour of microgrids by simulating the interactions of components like PV arrays, wind turbines, and batteries. Additionally, Simulink's toolbox is highlighted as a powerful environment for simulating complex systems, including microgrids. [22] The results indicate that simulation was used to predict demand values. The accuracy of these predictions is reported to be 99.91%, showcasing the effectiveness of the simulation approach in forecasting energy demand. Additionally, MATLAB code execution is mentioned for obtaining forecast and actual demand values, which implies a simulation aspect in the analysis. [39] It emphasizes the importance of simulation-based optimization methods, which are crucial for developing objective functions related to energy usage and thermal comfort. The paper also notes that both surrogate-based and simulation-based approaches are still active research areas due to their high computational costs. [40] The authors simulate various AMI architectures across five demographic regions. The results demonstrate that the proposed hybrid architecture outperforms both centralized and decentralized architectures in terms of load and geographic scalability. [41] The paper describes a simulation of an industrial energy audit where smart meters were installed to collect data. This data was analyzed using custom software, demonstrating the application of simulation techniques to assess energy consumption patterns. [42] The Gridstream system, a smart-metering solution, was evaluated through simulations using the OMNeT++ simulator, demonstrating its reliability and effectiveness in achieving high success rates for meter readings. [43] The

authors evaluate the performance of their proposed model through simulations. They compare the results of their model against a referenced model and a normal consumption pattern, which helps in assessing the effectiveness of their approach. [23] The paper does not mention the simulation, the methodologies have discussed, like machine learning methods, can be applied in simulation scenarios to predict energy consumption concepts and evaluate the impact of different sides on grid performance. [44] The researchers simulate different network configurations by creating a group of solutions, that can enhance the mutation and selection procedures. All can allow optimal energy efficiency exploration by different base station placements and configurations. [45] This study gives the results of simulation which determine the effectiveness of the optimization shape in scheduling machines, explain that the energy scheduling could be determined simultaneously for different kinds of machines. [34] This study has got a case study depend on real data of power grid from a different European region with two kinds of consumers industrial and residential. The method clears by using MATLAB simulations, that appeared an error margin near by 1% in normal situation and the highest error percent is 15% under exceptional conditions. The support vector machines (SVM) and other machine learning models were compared by results, demonstrating that the proposed frequency feature-based method (ECF) outperforms traditional approaches in energy forecasting.

Data Analysis: [21] This study confirms the relationship between weather forecasts and energy production to optimize microgrid performance. The analysis tools are mentioned too, which assess the changes in system configuration on energy outputs and costs. [22] This study shows the data analysis via the checking of demand variations over specific time intervals. To curve fitting it uses polynomial regression, which is a kind of data analysis to clarify the demand shapes. The analysis was accurate by visualize the demand variations and fitting curves. [39] The researchers discussing the data-driven probabilistic machine learning ways, which are include the analyzing energy networks and systems. they mention the use of machine learning (ML) for predicting energy consumption and costs, also the integration of huge data analytics in smart grid. [40] The study shows the collecting and analyzing massive smart meters data (SMs). The networks have to process this huge data to correspond the smart grid needs. [41] The study addresses how could smart meters identify energy-intensive machines and processes, to let comparisons against industry benchmarks for energy conservation. Therefore, the study talks about the use of load cycle analysis to capture

instantaneous power draws, which helps in understanding system interactions and enhancing the efficiency. [42] The study shows the rule of data analysis in understanding the management of different network technologies and if it is appropriate for smart-metering systems, as it shows available options for effective communication. [43] The way of analysis done by examining the performance metrics like the Peak-to-Average Ratio (PAR) to clarify the scheduling model on energy consumption shapes. The results show a decrease in the cost of energy and enhanced require management. [23] The study focuses on data analysis, different analytical procedures used to change a raw smart meter data into concrete data. This involves descriptive, predictive, and prescriptive analytics, that are important for clarify consumption ways and making the decisions. [44] The study shows the data analysis of different wireless technologies and introducing metrics by designing the power consumption for example power consumption per covered area (P C area). This analysis helps compare the energy efficiency of various technologies across different bit rates. [45] is implicitly involved in the optimization and simulation processes, as the framework relies on real-time price information and user preferences to make scheduling decisions. The analysis of energy consumption patterns and user satisfaction is crucial for the optimization objectives outlined in the paper. [34] The document provides an in-depth analysis of electricity consumption data using smart meters. It highlights the role of real-time data acquisition and processing in optimizing power distribution. The forecasting model is built on historical consumption trends, using Artificial Intelligence (AI) techniques, regression models, and empirical mode decomposition (EMD). The study confirms that hybrid forecasting models combining AI and statistical methods yield the most accurate results, particularly in balancing renewable energy integration and addressing uncertainties in energy supply and demand.

2.3 CASE STUDIES AND PREVIOUS RESEARCHES

Here the summarize similar studies from different regions, focusing on optimization, simulation, and data analysis:

In Spain, Hernández Rodríguez et al. (2023) employed artificial intelligence models to predict energy pricing and its impact on electricity consumption. Their study demonstrated that advanced machine learning techniques could effectively forecast energy prices, thereby aiding in better consumption planning and cost savings for consumers. [46].

Similarly, a study by Alonso et al. (2019) introduced a scalable Long Short-Term Memory (LSTM) model for short-term forecasting of disaggregated electricity loads. The model was capable of accurately predicting individual consumer loads, showcasing its potential for large-scale applications in energy management. [47].

In China, the research emphasizes the significance of effective demand-side management strategies to enhance grid stability and efficiency, particularly during peak load periods. The study estimates annual benefits of 13 billion yuan from demand response initiatives and proposes five mechanisms for allocating national targets to different provinces. It also highlights that 19:00 is the most critical time for implementing demand response activities in most regions. [48].

Dubai, United Arab Emirates A study analysed residential electricity consumption patterns using 15-minute interval smart meter data from 369 households in Dubai. The research identified distinct consumption behaviours and peak demand periods, emphasizing the influence of external temperatures on energy usage. These insights are instrumental in formulating targeted energy-saving strategies and demand-side management initiatives. [49].

Republic of Ireland Researchers employed machine learning algorithms to predict residential electricity consumption patterns based on smart meter and household data. The study revealed that factors such as temperature, day of the week, and seasonal variations significantly impact electricity usage. Clustering techniques identified six distinct intra-day load profiles, providing a foundation for personalized energy management approaches. [50].

London, United Kingdom the Low Carbon London project utilized big data analytics with Apache Spark to enhance load forecasting and demand response in the smart grid. By analyzing extensive smart meter datasets, the study developed scalable models that improved the accuracy of load predictions. These models support the efficient integration of renewable energy sources and the implementation of dynamic time-of-use tariffs. [51].

These case studies provide valuable insights and establish a solid foundation for applying similar methodologies in Al Khums. The relation between all the studies is the vital role of

smart meters' through data-driven simulation and optimization techniques to make it better in efficiency and reliability of energy systems.

2.4 DATA SIMULATION IN POWER CONSUMPTION STUDIES

The modern electrical power systems become more difficult to understand, due to the integration of renewable energy sources and the widely uses of smart grid technologies has confirmed the use of advanced data simulation methods. These methods have got a vital role in optimizing power consumption, analysing and, modelling, to allow engineers studying system approaches under various scenarios.

Simulation methods represent a powerful core for predicting how they respond to change in load and the dynamics of electrical systems, weather conditions, and user lifestyle. Monte Carlo simulation is one of the most widely used method in electrical engineering, it uses probabilistic models and random sampling to help system reliability and how to do it. This method is specially good at uncertainty analysis, like in evaluating load demand and system failure rates (Billinton & Allan, 1996). [52]. Another study about-based modelling (ABM). Which is used to simulate the methods of distributed energy resources, control machines and consumer appliances. ABM collects the interactions between these agents and make it easy for a more real simulation of demand-side management and energy efficiency strategies (Palensky & Dietrich, 2011). [53]. Newly studies in ML have more simulation capabilities enhancement. Algorithms such as artificial neural networks (ANNs) and SVMs have detected accuracy in predicting power consumption dependent on previous data. These models allow simulate consumption under different situations, letting them invaluable for energy role and actual-time (Hippert, Pedreira, & Souza, 2001). [54]. To employ for simulating the electrical characteristics of power systems there are some software tools you can count on them like MATLAB/Simulink, and ETAP, these tools are supported of loads, generators, transmission lines, and renewable energy, so it will be easy to comprehensive analysis of control strategies, system dynamics, and stability. (Glover, Sarma, & Overbye, 2012). [55].

These simulation technology applications are widely to use. They include optimizing energy consumption in residential and commercial buildings, evaluating the impact of electric vehicles on grid demand, assessing the benefits of energy storage systems, and planning for

the integration of distributed generation. By enabling predictive analysis and proactive decision-making, data simulation contributes significantly to the development of efficient, resilient, and sustainable power systems.

2.5 GAPS IN EXISTING LITERATURE

Most studies on smart meter implementation and energy optimization are conducted in developed nations or large cities in emerging economies. There is a noticeable absence of localized studies focusing on Libya, and Al Khums in particular. This makes it hard to generalize global findings to local conditions—especially given Libya’s unique infrastructure and socio-political context.

By analysing reference [46], it has gaps which will be compared to the current study:

2.5.1 Limited Exploration of Intraday Market Dynamics

In Hernández Rodríguez et al. (2023) [46]: The study uses hourly data for predictions but does not deeply explore intraday market dynamics, such as real-time trading adjustments or market-specific volatility, leaving a gap in understanding their influence on forecasts. While this research leverages simulated smart meter data to model real-time data collection at 15-minute intervals, a significant improvement over the hourly granularity in Hernández Rodríguez et al. This finer resolution enables a closer examination of intraday consumption patterns and anomalies. By simulating smart meter capabilities, this study captures short-term fluctuations that could reflect intraday market dynamics.

2.5.2 Lack of Tail Performance Analysis

In Hernández Rodríguez et al. (2023) [46]: The study proposes but does not implement tail performance measures (e.g., Kupiec test) to evaluate model behaviour during extreme events like price spikes or unusual consumption shifts, limiting reliability assessment in volatile conditions. While in the methodology, it includes anomaly detection and fault diagnosis using smart meter data analytics, which identifies abnormal load behaviours. For instance, it simulates scenarios with hypothetical active power drops to detect unusual consumption shifts. However, in this study analysis does not explicitly employ statistical tail performance measures like the Kupiec test or assess model reliability during extreme events beyond

descriptive detection. The study focus' is on practical anomaly identification rather than formal statistical validation of tail risks, which aligns with the simulation-based approach but leaves a gap in rigorous extreme-event evaluation.

2.5.3 Exclusion of External Variables

In Hernández Rodríguez et al. (2023) [46]: The reliance on historical price and consumption data, without integrating external variables like weather, economic indicators, or policy shifts, restricts the models' ability to capture real-world complexities. While this study primarily uses simulated smart meter data based on electrical parameters extracted from a regular meter in Al Khums. While this study emphasizes real-time monitoring and load profiling, there's limited evidence of integrating external variables like weather or economic factors into your simulations. linked load increases to high temperatures in August, suggesting potential for weather integration when historical climate data is available.

2.5.4 Absence of Real-Time Application Testing

In Hernández Rodríguez et al. (2023) [46]: The models rely on historical data (2014–2022) without real-time application testing, raising questions about adaptability to current or future conditions. While this study uses simulated smart meter data rather than historical datasets, modelling real-time collection at 15-minute intervals. This simulation mimics real-time capabilities, contrasting with the static historical approach of Hernández Rodríguez et al. the study compares smart meter performance to traditional meters, highlighting advantages like rapid data transmission and anomaly detection, which suggest operational adaptability.

2.5.5 Exclusive Focus on Short-Term Forecasts

In Hernández Rodríguez et al. (2023) [46]: The study focuses on hourly intraday forecasts, neglecting longer-term predictions (e.g., weekly, monthly, yearly), which are vital for comprehensive energy planning and policy-making. While this research emphasizes short-term load analysis and forecasting, such as instantaneous and very short-term load forecasting (VSTLF) at 15-minute intervals. However, it also addresses broader forecasting categories enabled by smart meters, including short-term (STLF), medium-term load forecasting (MTLF), and long-term (LTLF) load forecasting, the study focus' on load profiling, and demand management further supports longer-term grid optimization

strategies, aligning with Al Khums' need for sustainable energy planning. While the simulations prioritize short-term granularity, the framework in this study propose is scalable to longer horizons, unlike the exclusive intraday focus in Hernández Rodríguez et al. (2023).



3. METHODOLOGY

3.1 RESEARCH DESIGN AND APPROACH

3.1.1 Extracting Data from One of the Regular Electronic Meters

Electronic meters installed in the city of Al Khums (Data Readout - Current values) which can be extracted via (HDMI connection) or via (hand held) and both are connected to a computer with the program for the type of meter loaded. Extracted data tables (Appendix A).

From the Table 3.1 the data provided by the meter is as follows:

First: (Data Readout - Current values)

Indicates that the data is current data for all variables that were measured, i.e. they were measured at the time and date indicated in column No. 2

Second: Device identification: *****

Indicates the type and number of the meter and was hidden for ethical considerations.

Third: The third column (Ident) is the variable code and the sixth column (Description) is the description of the variable code.

Fourth: The fourth and fifth columns (Value) and (Unit) are the value of the variable and its unit of measurement.

After we have identified the types of data that can be extracting from the meter, we move on to examine the values of the first variable and know its technical implications.

a. Total Active Energy

Table 3.1: Shows the Total Active Energy.

	Time	Ident	Value	Unit	Description
1	06/08/2024 13:43	0- 0:96.1.0*255	***** *	Unknown	Device ID 1, manufacturing number
2	06/08/2024 13:43	1-0:1.8.0*255	418182042.5	Watt hour (Wh)	Active energy import (+A)
3	06/08/2024 13:43	1- 0:21.8.0*255	152747059.8	Watt hour (Wh)	Active energy import (+A) L1

Table 3.1: Shows the Total Active Energy “Table Continued”.

4	06/08/2024 13:43	1- 0:41.8.0*255	139381600. 1	Watt hour (Wh)	Active energy import (+A) L2
5	06/08/2024 13:43	1- 0:61.8.0*255	126053859. 4	Watt hour (Wh)	Active energy import (+A) L3
6	06/08/2024 13:43	1-0:2.8.0*255	1.5	Watt hour (Wh)	Active energy export (-A)
7	06/08/2024 13:43	1- 0:22.8.0*255	1.8	Watt hour (Wh)	Active energy export (-A) L1
8	06/08/2024 13:43	1- 0:42.8.0*255	43	Watt hour (Wh)	Active energy export (-A) L2
9	06/08/2024 13:43	1- 0:62.8.0*255	465.7	Watt hour (Wh)	Active energy export (-A) L3

From Table 3.1 in row No. 2, we find that the total value of the variable (Active energy import (+A)) is (418182042.5Wh) which is the sum of the values in the 3 phases shown in row No. 3, 4 and 5. This variable is the value of the Active energy in the positive direction (Import) (the positive direction is described here as the direction from (utility) to (load)). In contrast, row No.6 represents the same variable (Active energy export (-A)) with value (1.5Wh) but in the negative direction (Export), (The negative direction is described here as the direction from (load) to (utility)).

b. Total Reactive Energy

Table 3.2: Shows the Total Reactive Energy.

	Time	Ident	Value	Unit	Description
1	06/08/2024 13:43	1-0:3.8.0*255	289355135. 8	Var hour (varh)	Reactive energy import (+R)
2	06/08/2024 13:43	1- 0:23.8.0*255	90176758.4	Var hour (varh)	Reactive energy import (+R) L1
3	06/08/2024 13:43	1- 0:43.8.0*255	100741939. 3	Var hour (varh)	Reactive energy import (+R) L2
4	06/08/2024 13:43	1- 0:63.8.0*255	98549786.1	Var hour (varh)	Reactive energy import (+R) L3

Table 3.2: Shows the Total Reactive Energy “Table Continued”.

5	06/08/2024 13:43	1-0:4.8.0*255	615404.3	Var hour (varh)	Reactive energy export (-R)
6	06/08/2024 13:43	1-0:24.8.0*255	668162.7	Var hour (varh)	Reactive energy export (-R) L1
7	06/08/2024 13:43	1-0:44.8.0*255	33616.7	Var hour (varh)	Reactive energy export (-R) L2
8	06/08/2024 13:43	1-0:64.8.0*255	26996.6	Var hour (varh)	Reactive energy export (-R) L3

From Table 3.2 in row No. 1, we find that the total value of the variable (Reactive energy import (+R)) is (289355135.8varh) which is the sum of the values in the 3 phases shown in row No. 2, 3 and 4. This variable is the value of the Reactive energy in the positive direction (Import) (the positive direction is described here as the direction from (utility) to (load)). In contrast, row No.5 represents the same variable (Reactive energy export (-R)) with value (615404.3varh) but in the negative direction (Export), (The negative direction is described here as the direction from (load) to (utility)).

c. Total Apparent energy

Table 3.3: Shows the Total Apparent Energy.

	Time	Ident	Value	Unit	Description
1	06/08/2024 13:43	1-0:9.8.0*255	517055598.5	Volt-ampere hour (VAh)	Apparent energy import (+VA)
2	06/08/2024 13:43	1-0:29.8.0*255	181149159.7	Volt-ampere hour (VAh)	Apparent energy import (+VA) L1
3	06/08/2024 13:43	1-0:49.8.0*255	173854335.1	Volt-ampere hour (VAh)	Apparent energy import (+VA) L2
4	06/08/2024 13:43	1-0:69.8.0*255	162054318.8	Volt-ampere hour (VAh)	Apparent energy import (+VA) L3
5	06/08/2024 13:43	1-0:10.8.0*255	67.5	Volt-ampere hour (VAh)	Apparent energy export (-VA)
6	06/08/2024 13:43	1-0:30.8.0*255	75.2	Volt-ampere hour (VAh)	Apparent energy export (-VA) L1
7	06/08/2024 13:43	1-0:50.8.0*255	436.6	Volt-ampere hour (VAh)	Apparent energy export (-VA) L2
8	06/08/2024 13:43	1-0:70.8.0*255	1802.7	Volt-ampere hour (VAh)	Apparent energy export (-VA) L3

From Table 3.3 in row No. 1, we find that the total value of the variable (Apparent energy import (+VA)) is (517055598.5VAh) which is the sum of the values in the 3 phases shown

in row No. 2, 3 and 4. This variable is the value of the Apparent energy in the positive direction (Import) (the positive direction is described here as the direction from (utility) to (load)). In contrast, row No.5 represents the same variable (Apparent energy export (-VA)) with value (67.5Vah) but in the negative direction (Export), (The negative direction is described here as the direction from (load) to (utility)).

d. Voltage

Table 3.4: Shows the Voltage.

	Time	Ident	Value	Unit	Description
1	06/08/2024 13:43	1-0:32.28.0*255	214	Volt (V)	Average voltage Time integral 6 L1
2	06/08/2024 13:43	1-0:52.28.0*255	215	Volt (V)	Average voltage Time integral 6 L2
3	06/08/2024 13:43	1-0:72.28.0*255	215	Volt (V)	Average voltage Time integral 6 L3
4	06/08/2024 13:43	1-0:32.7.0*255	204	Volt (V)	Instantaneous voltage L1
5	06/08/2024 13:43	1-0:32.7.124*255	0	Percent (%)	Instantaneous voltage L1 THD
6	06/08/2024 13:43	1-0:52.7.0*255	205	Volt (V)	Instantaneous voltage L2
7	06/08/2024 13:43	1-0:52.7.124*255	0.9	Percent (%)	Instantaneous voltage L2 THD
8	06/08/2024 13:43	1-0:72.7.0*255	206	Volt (V)	Instantaneous voltage L3
9	06/08/2024 13:43	1-0:72.7.124*255	1.6	Percent (%)	Instantaneous voltage L3 THD

From Table 3.4 in row No. 1, we find that the value of the voltage (214V) is (Average value) but in the row No. 4 is (Instantaneous value) (204 V) for the same phase (L₁), row No. 2, show that the value of the voltage (215V) is (Average value) but in the row No. 6 is (Instantaneous value) (205V) for the same phase (L₂), row No. 3, show that the value of the voltage (215V) is (Average value) but in the row No. 8 is (Instantaneous value) (206 V) for the same phase (L₃).

We see here a new variable which is very important as we will discuss in the analysis, row No. 5,7, and 9, represent THD voltage (Total Harmonic Distortion), It is the percentage of distortion in the voltage in each phase separately.

e. Current

Table 3.5: Shows the Current.

	Time	Ident	Value	Unit	Description
1	06/08/2024 13:43	1-0:31.28.0*255	145	Ampere (A)	Average current Time integral 6 L1
2	06/08/2024 13:43	1-0:51.28.0*255	138	Ampere (A)	Average current Time integral 6 L2
3	06/08/2024 13:43	1-0:71.28.0*255	161	Ampere (A)	Average current Time integral 6 L3
4	06/08/2024 13:43	1-0:31.7.0*255	206	Ampere (A)	Instantaneous current L1
5	06/08/2024 13:43	1-0:31.7.124*255	3.1	Percent (%)	Instantaneous current L1 THD
6	06/08/2024 13:43	1-0:51.7.0*255	197	Ampere (A)	Instantaneous current L2
7	06/08/2024 13:43	1-0:51.7.124*255	11	Percent (%)	Instantaneous current L2 THD
8	06/08/2024 13:43	1-0:71.7.0*255	239	Ampere (A)	Instantaneous current L3
9	06/08/2024 13:43	1-0:71.7.124*255	0	Percent (%)	Instantaneous current L3 THD

From Table 3.5 in row No. 1, we find that the value of the current (145A) is (Average value)but in the row No. 4 is (Instantaneous value) (206A) for the same phase (L₁) , row No. 2, show that the value of the current (138A) is (Average value) but in the row No. 6 is (Instantaneous value) (197A) for the same phase (L₂), row No. 3, show that the value of the current (161A) is (Average value) but in the row No. 8 is (Instantaneous value) (239A) for the same phase (L₃), row No. 5,7, and 9, represent THD current (Total Harmonic Distortion), It is the percentage of distortion in the current in each phase separately.

f. Frequency

Table 3.6: Shows the Frequency.

	Time	Ident	Value	Unit	Description
1	06/08/2024 13:43	1-0:14.7.0*255	49.9	Hertz (Hz)	Instantaneous net frequency: any phase

The electrical frequency value for most networks is 50 Hz, as the frequency in the Libyan network and most North African countries and it may differ in some Asian and European countries to become 60 Hz. The stability of the network frequency is a criterion for the safety of the network.

g. Power factor

Table 3.7: Shows the Power Factor.

	Time	Ident	Value	Unit	Description
1	06/08/2024 13:43	1- 0:13.5.0*255	0.885	Count	Last average power factor (+A/+VA)
2	06/08/2024 13:43	1- 0:33.5.0*255	0.902	Count	Last average power factor (+A/+VA) L1
3	06/08/2024 13:43	1- 0:53.5.0*255	0.867	Count	Last average power factor (+A/+VA) L2
4	06/08/2024 13:43	1- 0:73.5.0*255	0.883	Count	Last average power factor (+A/+VA) L3
5	06/08/2024 13:43	1- 0:84.5.0*255	0	Count	Last average power factor negative (-A/-VA)
6	06/08/2024 13:43	1- 0:85.5.0*255	0	Count	Last average power factor negative (-A/-VA) L1
7	06/08/2024 13:43	1- 0:86.5.0*255	0	Count	Last average power factor negative (-A/-VA) L2
8	06/08/2024 13:43	1- 0:87.5.0*255	0	Count	Last average power factor negative (-A/-VA) L3

Power factor is one of the important variables to study in the electrical analysis of any load, if not the most important one at all. Electrically, it is the cos of the angle between voltage and current, but on a broader scale, its value and sign indicate the type of load, the integrity of electrical connections, and the direction of consumption. Rows No. 1,2,3 and 4 indicate the average value of the power factor in the positive direction, where rows No. 5,6,7, and 8 indicate the average value of the power factor in the negative direction.

h. Demand

Table 3.8: Shows the Demand.

	Time	Ident	Value	Unit	Description
1	06/08/2024 13:43	1- 0:1.5.0*25 5	90922. 8	Watt (W)	Last average demand register - Active energy import (+A)
2	06/08/2024 13:43	1- 0:2.5.0*25 5	0	Watt (W)	Last average demand register - Active energy export (-A)
3	06/08/2024 13:43	1- 0:3.5.0*25 5	44995. 2	Var	Last average demand register - Reactive energy import (+R)
4	06/08/2024 13:43	1- 0:4.5.0*25 5	0	Var	Last average demand register - Reactive energy export (-R)
5	06/08/2024 13:43	1- 0:9.5.0*25 5	10187 2.2	Volt-ampere (VA)	Last average demand register - Apparent energy import (+VA)
6	06/08/2024 13:43	1- 0:10.5.0*2 55	0	Volt-ampere (VA)	Last average demand register - Apparent energy export (-VA)

The average demand in electrolysis is an indispensable cornerstone, as without it, the true amount of electricity consumed monthly cannot be imagined, and without its continuous observation, any future loads cannot be predicted. The values in the rows No. 1,3, and 5 represent the (P, Q, S) in the positive direction, while the rows No. 2,4, and 6 represent the same variables in the negative direction in order.

3.1.2 Descriptive Analytics for Different Parameters

Descriptive analytics for different parameters such as effective and ineffective consumption, current, voltage and energy trends technically using the significance of numbers.

3.1.2.1 Total active energy

The Table 3.1 directly indicates only two directions for the paths, either positive or negative. The positive direction in this case indicates the main direction from the network to the load (import) and the reverse direction from the load to the network is (export). In fact, it may not be understood by ordinary people that the load can send active Energy to the network. This is illogical unless the load is connected to another source such as solar cells or generators. In the absence of this, the presence of large values in the negative direction means that there is a defect in the meter connections (resulting from tampering and an attempted theft or from a technical error in installing the meter). Accordingly, large values in the negative direction indicate a defect or problem that requires going again to the load site.

3.1.2.2 Total reactive energy

In the same steps, we find that Table 3.2 has only two directions, positive and negative, the positive direction is coming from the network to the load (import) and the reverse direction is coming from the load to the network (export), and the decisive point here is that the reactive energy is the inductive reaction of the installed loads, it occupies a space from the total apparent energy and is consumed in the form of heat and loss in the network, it is compensated by installing capacitor units on the loads until these values are reduced.

The large values in the positive direction indicate:

- 1- The presence of a high inductive load at the consumer (such as induction motors or electric furnaces or welding equipment... etc. inductive loads) and this is a strong indicator to conclude the type of load.
- 2- The absence of compensatory capacitor units to improve the energy efficiency of the customer.
- 3- Without the presence of energy efficiency improvement units, the transformer feeding such a type of load will be in an ineffective load state and cannot be exploited well.

The relationship between apparent power (S), active power (P), and reactive power (Q) is given by the equation:

$$S^2 = P^2 + Q^2 \quad (3.1)$$

And it also Calculated by:

$$Q = V \times I \times \sin \theta \quad (3.2)$$

Where: Q : is the reactive power in volt-amperes reactive (VAR), V : is the voltage, I : is the current, θ : is the phase angle between the voltage and the current. Returning to Table 3.2 we find that values indicate the reactive energy, which is the parameter multiplied by the number of hours, in addition to being cumulative values. The same values can be obtained, but in greater detail, clarifying whether the reactive energy is the result of inductive loads or an increase in capacitive loads or units based on the energy quarters. This is what Table 3.9 shows.

Table 3.9: Shows the Reactive Energy in Power Quarters.

	Time	Ident	Value	Unit	Description
1	06/08/2024 13:43	1-0:5.8.0*255	289355133.5	Var hour (varh)	Reactive energy QI (+Ri)
2	06/08/2024 13:43	1-0:25.8.0*255	90176744.1	Var hour (varh)	Reactive energy QI (+Ri) L1
3	06/08/2024 13:43	1-0:45.8.0*255	100741523.9	Var hour (varh)	Reactive energy QI (+Ri) L2
4	06/08/2024 13:43	1-0:65.8.0*255	98548130.8	Var hour (varh)	Reactive energy QI (+Ri) L3
5	06/08/2024 13:43	1-0:6.8.0*255	2.2	Var hour (varh)	Reactive energy QII (+Rc)
6	06/08/2024 13:43	1-0:26.8.0*255	14.3	Var hour (varh)	Reactive energy QII (+Rc) L1
7	06/08/2024 13:43	1-0:46.8.0*255	415.3	Var hour (varh)	Reactive energy QII (+Rc) L2
8	06/08/2024 13:43	1-0:66.8.0*255	1655.1	Var hour (varh)	Reactive energy QII (+Rc) L3
9	06/08/2024 13:43	1-0:7.8.0*255	0	Var hour (varh)	Reactive energy QIII (-Ri)
10	06/08/2024 13:43	1-0:27.8.0*255	1	Var hour (varh)	Reactive energy QIII (-Ri) L1
11	06/08/2024 13:43	1-0:47.8.0*255	1.2	Var hour (varh)	Reactive energy QIII (-Ri) L2

Table 3.9: Shows the Reactive Energy in Power Quarters “Table Continued”.

12	06/08/2024 13:43	1-0:67.8.0*255	4.9	Var hour (varh)	Reactive energy QIII (-Ri) L3
13	06/08/2024 13:43	1-0:8.8.0*255	615403.9	Var hour (varh)	Reactive energy QIV (-Rc)
14	06/08/2024 13:43	1-0:28.8.0*255	668161.7	Var hour (varh)	Reactive energy QIV (-Rc) L1
15	06/08/2024 13:43	1-0:48.8.0*255	33615.2	Var hour (varh)	Reactive energy QIV (-Rc) L2
16	06/08/2024 13:43	1-0:68.8.0*255	26991.7	Var hour (varh)	Reactive energy QIV (-Rc) L3

The values in the first four rows, 1-4 indicate the value of the reactive energy in the first quarter with a positive sign, which is a clear indication that the consumer loads are inductive loads.

The values in the four rows that follow, 5-9, indicate the value of the capacitive load at the consumer in the second quarter with a positive sign, which are also small values.

As for the four rows from 10-13, they indicate the inductive field coming from the network to the consumer, which may in fact be an inductive current for the transformer itself, and its values are small, as shown, and this is clear in the third quarter with a negative sign.

Up to the last 3 rows from 14-16, we see that the capacitive loads in the fourth quarter with a negative sign are an expression of the presence of a capacitor unit before the meter, which makes it have a negative sign.

3.1.2.3 Third total apparent energy

The apparent power is the balance that cannot be disturbed, it is the sum of the active and reactive power. Not to mention that the apparent power of the primary direction of any transformer is the same as the apparent power of the secondary direction. The following equations indicate the stability of the apparent power in both directions, as we will see in Eq.3.3 the relationship between apparent power (S), active power (P), and reactive power (Q) is given by the equation.

$$S^2 = P^2 + Q^2 \quad (3.3)$$

Where: P : is the active power, Q : is the reactive power.

The relationship between apparent power (S), current (I), and voltage (V) is given by the equation:

$$S = V \times I \quad (3.4)$$

Where: V : is the voltage, I : is the current. If we consider the example of the values from the Table 3.4 and Table 3.5 for phase 1(L1), and calculate the one side of transformer (secondary) which the meter installed on it.

$V_{1-L1} = 204V$, $V_{1-L1} = 204V$ on the secondary side and consuming a current off, $I_{1-L1} = 206A$, $I_{1-L1} = 206A$

then the apparent power on the secondary side is calculated as follows:

$$S_{1-L1} = V_{1-L1} \times I_{1-L1} = 204V \times 206A = 42024VA$$

We note that the value listed in Table 3.3 is a very large value and does not express these results for two reasons: the first is that the value of the apparent power in Table 3.3 is multiplied by the number of hours, and the second is that it is a cumulative value and not an instantaneous one. The real table that will express this calculated value is the table of instantaneous values of the apparent power as follows:

Table 3.10: Shows the Instantaneous Apparent Power.

	Time	Ident	Value	Unit	Description
1	06/08/2024 13:43	1- 0:9.7.0*255	132158.3	Volt-ampere (VA)	Instantaneous apparent import power (+VA)
2	06/08/2024 13:43	1- 0:29.7.0*25 5	42203.6	Volt-ampere (VA)	Instantaneous apparent import power (+VA) L1
3	06/08/2024 13:43	1- 0:49.7.0*25 5	40586	Volt-ampere (VA)	Instantaneous apparent import power (+VA) L2
4	06/08/2024 13:43	1- 0:69.7.0*25 5	49368.5	Volt-ampere (VA)	Instantaneous apparent import power (+VA) L3

Table 3.10: Shows the Instantaneous Apparent Power “Table Continued”.

5	06/08/2024 13:43	1- 0:10.7.0*25 5	0	Volt-ampere (VA)	Instantaneous apparent export power (-VA)
6	06/08/2024 13:43	1- 0:30.7.0*25 5	0	Volt-ampere (VA)	Instantaneous apparent export power (-VA) L1
7	06/08/2024 13:43	1- 0:50.7.0*25 5	0	Volt-ampere (VA)	Instantaneous apparent export power (-VA) L2
8	06/08/2024 13:43	1- 0:70.7.0*25 5	0	Volt-ampere (VA)	Instantaneous apparent export power (-VA) L3

Now we find that the calculated value is the same value extracted from the meter. It remains for us to know the value in the other direction so that we can infer many of the matters that will be mentioned, to obtain the value in the other direction, there must be a meter at the beginning of the line feeding the transformer to know the value of the apparent power in the primary and in general this can be expected through the same equation.

$$S_{2-L1} = V_{2-L1} \times I_{2-L1} = 11000V \times 3.8A = 42024VA$$

$V_{2-L1} = 11000V$ on the primary side and consuming a current of $I_{2-L1} = 3.8A$ Considering that the transformer under study is 11000/0.4, In this example, the apparent power on the primary and secondary sides is equal, which achieves the principle of energy conservation in the transformer.

Let's go further now, if the value measured on the meter at the beginning of the feeder differs (assuming that the feeder is for only one transformer) from the value measured on the meter in the transformer on the secondary side (the consumer side), then this is a clear indication of the presence of loads outside the meter if the feeder value is greater, and if it is less, this indicates a defect in one of the phases.

3.1.2.4 The voltage

Table 3.4 indicates 3 types of values for the same variable, which is: Initially, the average value of the voltage is an important value to determine the range in which the voltage moves, whether it is within the technically permissible limits or not.

The other value is the instantaneous value of the voltage, which indicates the presence or absence of voltage on the 3 phases instantaneously.

The last value is the percentage of the amount of distortion in the voltage wave, which is a very important factor in the network, as the presence of distortions in the voltage or current leads to many problems in the network, such as:

High temperature: Harmonics lead to increased energy loss in wires and electrical devices such as transformers and motors, which causes an increase in temperature.

Equipment damage: Harmonics can cause damage to electrical equipment due to their effects on electrical circuits.

Decreased efficiency: Harmonics may lead to a reduction in the efficiency of electrical systems due to increased losses.

Signal interference: Harmonics can cause interference in signals from other electronic devices or communication systems.

Sine wave interference: Harmonics lead to distortion of the shape of the sine wave, making the voltage and current in the system non-ideal.

3.1.2.5 The current

In the same pattern Table 3.5 indicates 3 types of values for the same variable, which is: Initially, the average value of the current is an important value to determine the range in which the current moves, whether it is within the expected limits or not.

The other value is the instantaneous value of the current, which indicates the presence or absence of current on the 3 phases instantaneously.

The last value is the percentage of the amount of distortion in the current wave, as the presence of distortions in the current leads as problems in the network.

3.1.2.6 The frequency

It is very important in power systems that the frequency is constant, as determining the frequency helps in controlling the operation of devices that depend on alternating current, such as transformers and motors. Some devices operate more efficiently when the frequency is constant. Table 3.6 indicates that the frequency is constant and the network is fine.

3.1.2.7 The power factor

Power Factor is a measure of how efficiently electrical energy is used in a system. It expresses the ratio between the active power that is used to perform actual work and the apparent power that represents the sum of the active and reactive power in the electrical system. So Power factor is the ratio of active power to apparent power in the system:

$$\text{Power Factor} = P/S \quad (3.5)$$

Where:

P : is the active power and is measured in watts (W).

S : is the apparent power and is measured in volt-amperes (VA).

How to Calculate Power Factor: Power factor can also be calculated using the phase angle (θ) between the voltage and current in the electrical circuit. Power factor is calculated using the relationship:

$$\text{Power Factor} = \cos(\theta) \quad (3.6)$$

Where:

θ : is the phase angle between voltage and current.

Power Factor 1 (or 100%): When the power factor is equal to 1, it means that all the power consumed in the system is being used effectively to do work (no power is wasted in generating magnetic or electric fields). This usually occurs in systems that contain purely resistive loads such as resistors.

Power Factor Less than 1: When the power factor is less than 1, it means that some of the power is being consumed in generating reactive power (such as electric motors or transformers) rather than being used in actual work. Inductive Loads (such as electric motors).

Negative Power Factor: Occurs when there is corrective reactive power, meaning that reactive power is being fed back into the grid.

Since it is a factor that determines energy efficiency, the value recorded in Table 3.7 which is 0.885 is a value that indicates that about 80% of the total apparent energy is utilized and about 20% of it is wasted in the form of inductive waves. This is a somewhat acceptable value, although it needs to be corrected with capacitors. What is unacceptable is for the

power factor to be less than 0.5. This is an indication of a fault in the meter connections or the absence of one of the variables, which necessitates reviewing the load being measured.

3.1.2.8 The demand

Looking at Table 3.8 we find that the table indicates the demand value for three variables, which are the active, reactive and apparent energy. The significance of knowing the average values is that we can verify that consumption is still within the safe operating limits of the transformer and the network or that the consumer is still within the contracted load.

3.2 SIMULATING THE SAME DATA FOR THE SAME METER

Simulating the same data for the same meter by using the same pattern for that extracted from HES, which is the server responsible for receiving the data sent by the smart meters (simulation in the same pattern using Python cods).

By using Python codes, it is possible to simulate what the range of data sent from the smart meter could be compared to the traditional meter and in the same pattern. The following figures show the simulated drawing of each of the previous electrical variables using a simulated model of Python codes. (Appendix B) .

Simulating Active Energy Data by Python

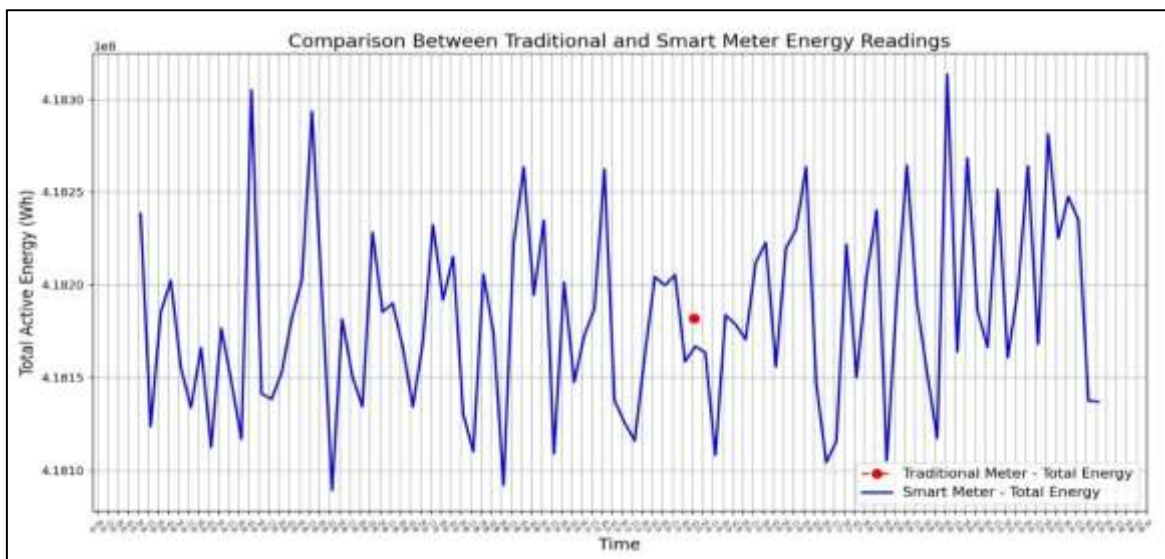


Figure 3.1: Shows the Simulating Data from Smart Meter Clarifying Total Active Energy.

From the diagram, we can see that the accuracy and availability of big data across time (from this variable Total Active Energy) provides two-way benefits. It is ideal for the customer to know when their consumption increases and the possibility of rationalizing this consumption. On the other hand, it is ideal for utility companies, as it provides a broader view and the possibility of managing demand for consumers within a specific area.

Simulating Reactive Energy Data by Python

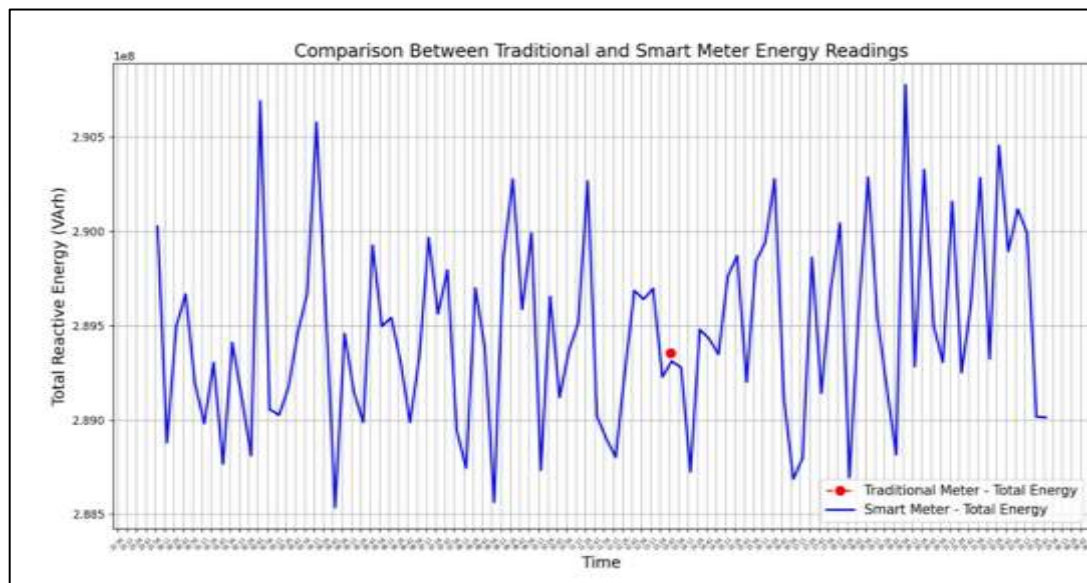


Figure 3.2: Shows the Simulating Data from Smart Meter Clarifying Total Reactive Energy.

Regarding Reactive consumption, the large dataset across time reveals another advantage of smart meters: identifying the amount of unused energy in the network as a whole. This data can then be used to determine the number and type of compensatory capacitors needed to reduce unused energy. Phases and operating times for each phase can also be automatically determined based on the time of highest Reactive consumption.

Simulating Apparent Energy Data by Python

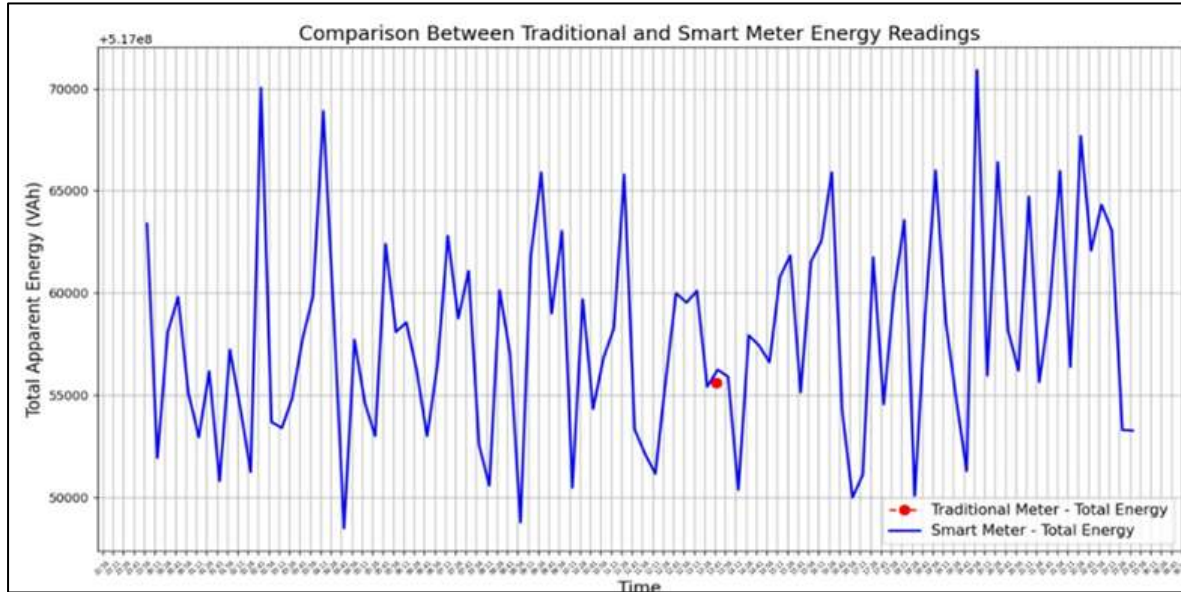


Figure 3.3: Shows the Simulating Data from Smart Meter Clarifying Total Apparent Energy.

Apparent energy data, on the other hand, provides a broader view. The more accurate the apparent energy data, the more precisely it can determine the actual percentage of transformers used in the network and the future percentage required based on times of increased apparent consumption. Example:

An area is supplied by an 11 kV feeder with six transformers, each with an apparent power of 500 kVA. This means that the actual installed power in this area is 3 MVA. Continuous measurement reveals that the apparent power consumed by the area at 1:00 PM is 2.2 MVA, while at the peak hour of 6:00 PM it is 2.7 MVA. This means that this area will need an increase in the number of transformers in the near future, especially if this measurement is for winter rather than summer. Other factors are taken into account when forecasting, but in general, apparent power readings are one of the pillars of forecasting.

Simulating Voltage Data by Python

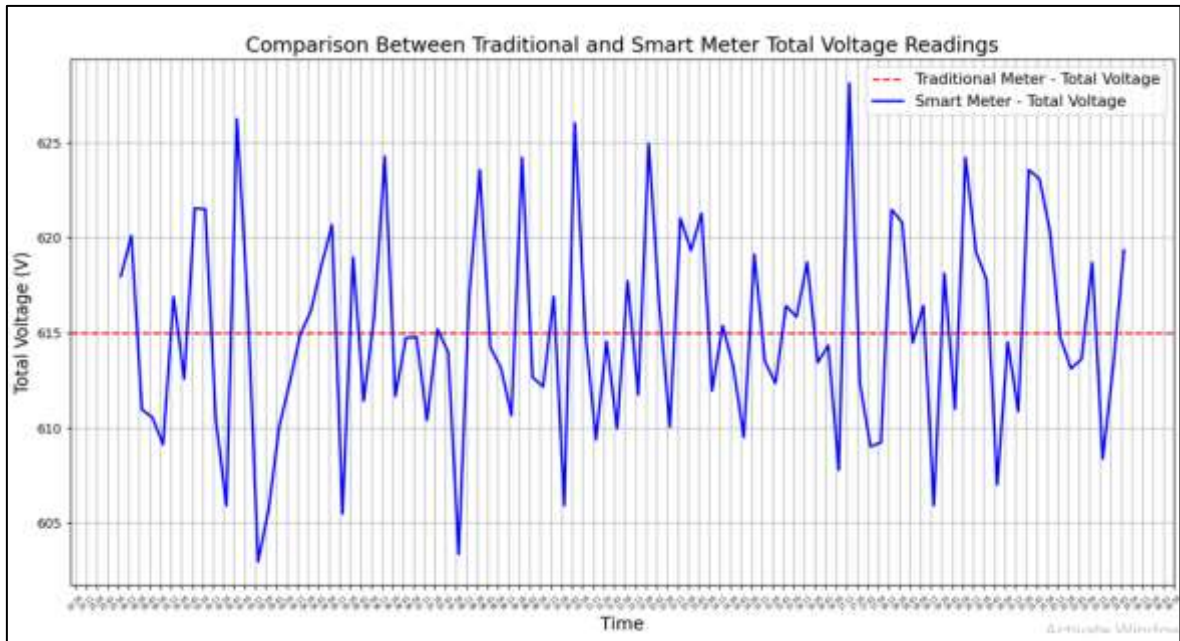


Figure 3.4: Shows the Simulating Data from Smart Meter Clarifying Voltage I.

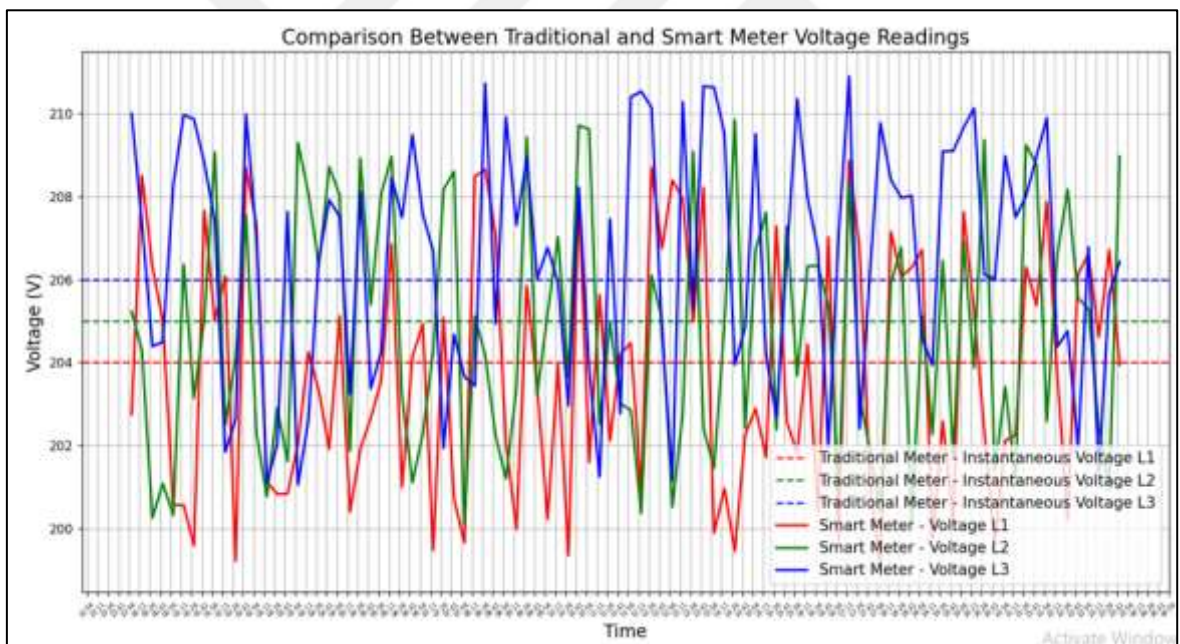


Figure 3.5: Shows the Simulating Data from Smart Meter Clarifying Voltage II.

The real-time voltage data, as shown in the (Figure 3.5), provides an accurate picture of the quality of the electrical supply reaching consumers and clearly indicates the locations and times when the voltage drops below the rated values. This makes it easier to quickly identify and address any weaknesses in the network.

Simulating Current Data by Python

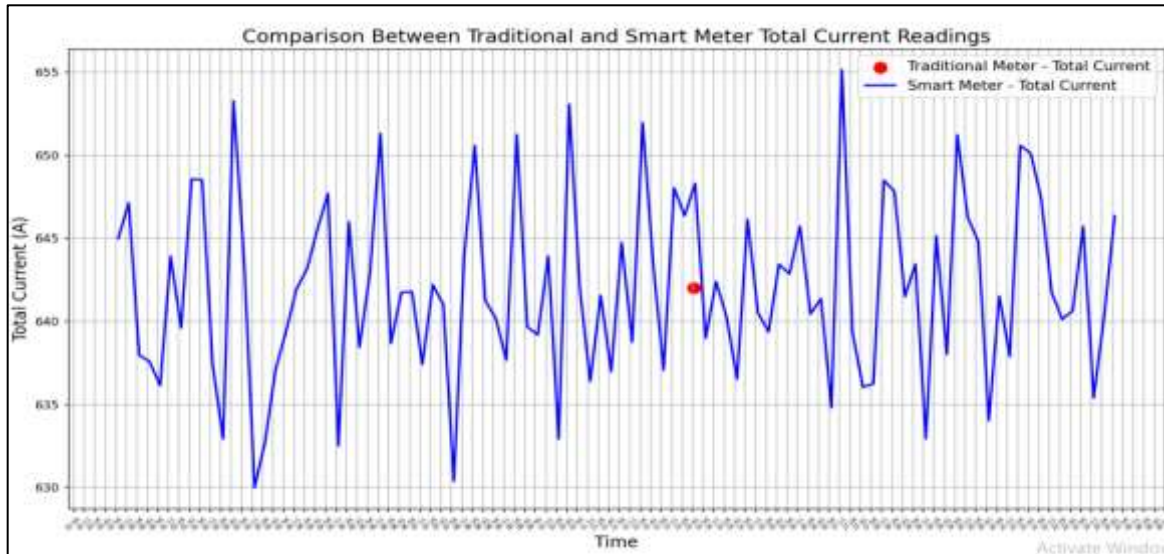


Figure 3.6: Shows the Simulating Data from Smart Meter Clarifying Current.

The advantages of real-time big data for current are similar to the advantages of active energy mentioned earlier in terms of load optimization for consumers and demand management for grid operators. However, a competitive advantage of current data is that grid operators can increase cable cross-section based on accurate monitoring of high peak loads. This is not possible with conventional meters, as some increased loads can damage components such as cables and switches.

Simulating Frequency Data by Python

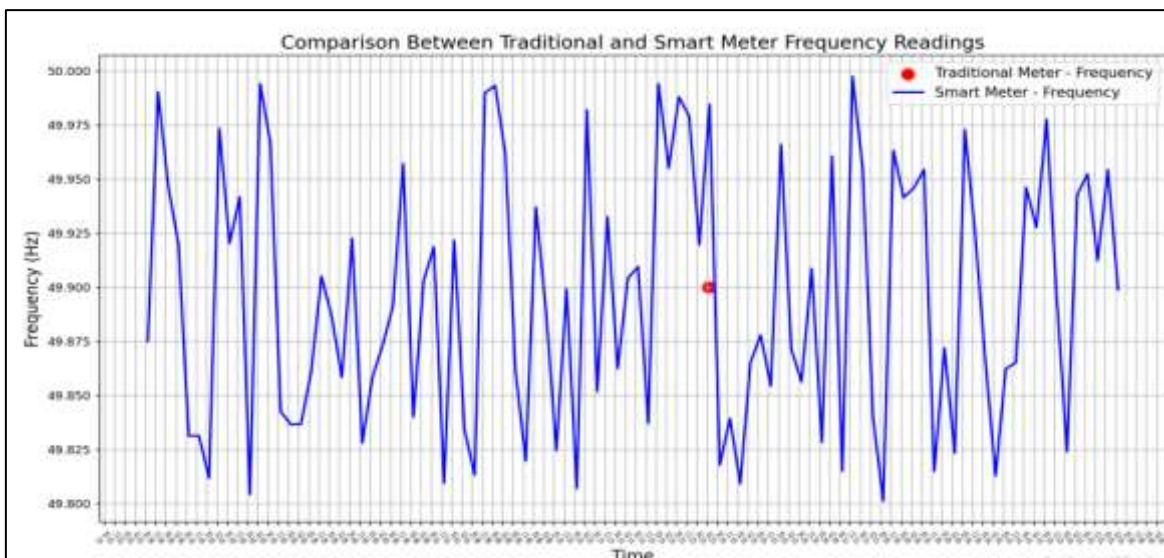


Figure 3.7: Shows the Simulating Data from Smart Meter Clarifying Frequency.

Regarding the frequency data shown in the (Figure 3.7), we find that monitoring frequency values is primarily to ensure the overall stability of the grid. Any frequency disturbance indicates a fault in the grid, so monitoring it continuously helps prevent deeper problems that may arise.

3.2.1 Smart Meter Data Analytics

We find that the paper (Yi Wang, et al) [23] contained more specific classifications for electrical analysis using smart meter data. It is also good to specify the purpose of electrical analysis as shown in (Figure 3.8) and as will be discussed in detail, but what was analysed in the previous part of the research will not differ much in its content, but it will become more specific, faster, accurate and more capable of being relied upon in smart meters for decision-making.

From another perspective, (Izilein, et al. 2024) [37], compared smart metering with traditional metering in the context of cost analysis and energy management. The results showed a decrease in the cost of electricity and the amount of energy delivered within 24 hours, as the developed smart metering system was tested on three different homes.

Thamer A. et al. (2020) [38], presented an integrated data framework for the Saudi Electricity Company (SEC) that includes pre-processing tools and techniques for analysing smart meter data. This framework uses real smart meter data and is tailored to different load patterns, such as residential, government, commercial, agricultural, and industrial. The developed framework receives raw data from smart meters, pre-processes it, and then performs the required analysis using the application layer. It has several benefits: simplifying unified data, unifying the spectrum of different data, and ultimately generating reliable and verified real-world data that can be used to implement various smart grid applications.

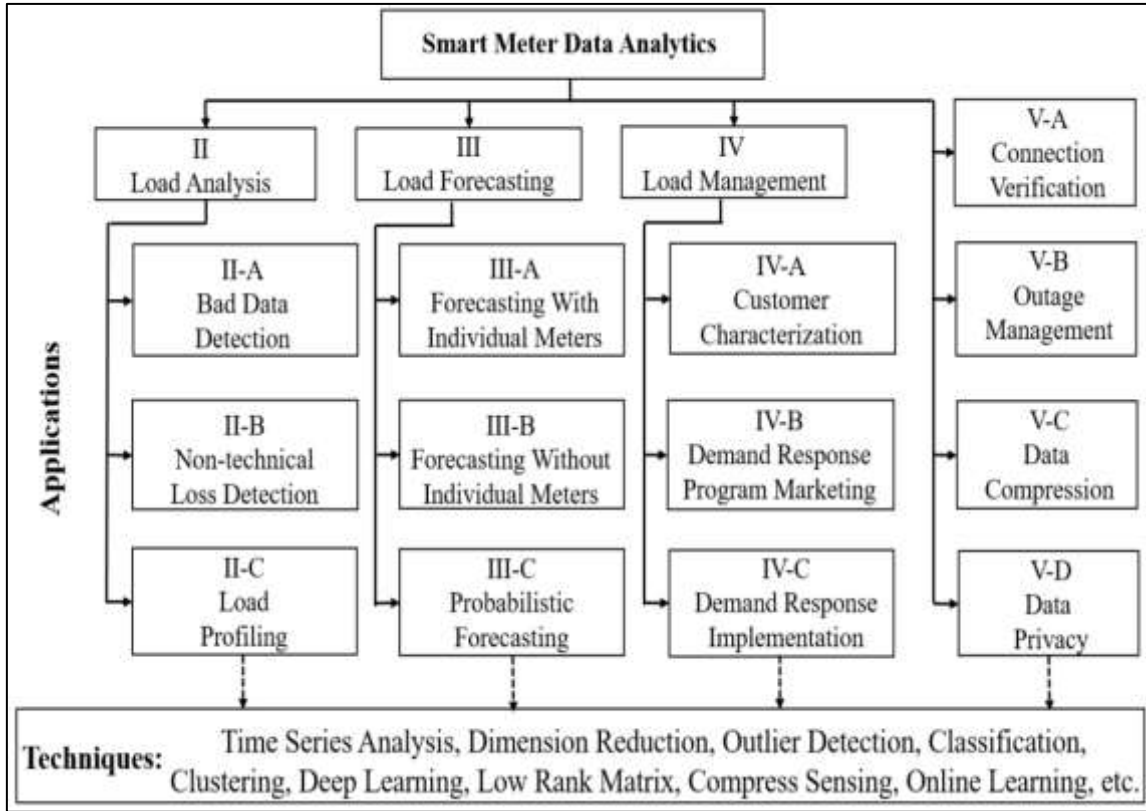


Figure 3.8: Shows the Applications of Data Analytics and Techniques.

3.2.1.1 Load analysis and forecasting

Smart meter data is extensively used for load analysis and forecasting. Descriptive analytics help in understanding consumption patterns, while predictive analytics forecast future loads. These insights are crucial for load management and optimizing energy distribution [23], [26].

3.2.1.2 Energy management systems

These systems leverage consumption data to optimize energy usage, enhance energy efficiency, and implement demand response strategies [26].

3.2.1.3 Anomaly detection and fault diagnosis

Detecting abnormal load behaviours and diagnosing faults in the power grid. by identify anomalies in consumption patterns, which helps in early detection of issues and improves grid reliability [24], [29].

3.2.1.4 Clustering and classification

Clustering methods, are applied to smart meter data to segment customers based on their consumption patterns. This segmentation aids in designing targeted tariffs and energy efficiency programs. Time series analysis and wavelets are used to improve clustering performance by accounting for data autocorrelation [25], [27], [28].

1. Load Analysis

why we should analyse the load parameters?

a. Detect Bad Data

Table 3.11 shows the Instantaneous active power, we saw in Table 3.3 that this variable has been extracted from the meter once at the date and time recorded in the table and recorded as cumulative value multiplied of hours. This is precisely the difference that the smart meter has from the meter mentioned above. The difference lies in the fact that the smart meter sends the reading of this variable every 15 minutes to the server system responsible for receiving the data. From here begins the journey of quantitative analysis of all this large data for only one variable over the course of only one day, for example. Accordingly, the server receives an amount of data that can be described as huge for all variables at all times. Returning to the modelling of active power, the assumption data recorded every 15 minutes as follows:

Table 3.11: Shows the Instantaneous Active Energy.

	Time	Ident	Value	Unit	Description
1	06/08/2024 13:43	1-0:1.7.0*255	11857 2.4	Watt (W)	Instantaneous active import power (+A)
2	06/08/2024 13:43	1-0:21.7.0*255	38214. 8	Watt (W)	Instantaneous active import power (+A) L1
3	06/08/2024 13:43	1-0:41.7.0*255	36133. 5	Watt (W)	Instantaneous active import power (+A) L2
4	06/08/2024 13:43	1-0:61.7.0*255	44224	Watt (W)	Instantaneous active import power (+A) L3

Table 3.11: Shows the Instantaneous Active Energy “Table Continued”.

5	06/08/2024 13:43	1-0:2.7.0*255	0	Watt (W)	Instantaneous active export power (-A)
6	06/08/2024 13:43	1-0:22.7.0*255	0	Watt (W)	Instantaneous active export power (-A) L1
7	06/08/2024 13:43	1-0:42.7.0*255	0	Watt (W)	Instantaneous active export power (-A) L2
8	06/08/2024 13:43	1-0:62.7.0*255	0	Watt (W)	Instantaneous active export power (-A) L3

That is, Table 3.11 will be repeated 4 times per hour, which will make the server operator (or computerized machine learning models) detect any change in the normal situation shown in the table. As we mentioned earlier, the presence of values in the negative direction means the presence of another source (which will be known from the consumer's contracts) or there is an attempt to steal the current, and this is the most common case, as many consumers do not have two sources for the same load. The feature of speed, accuracy and repetition of data for one of the variables at multiple times is one of the most important features of the smart meter. The following figure shows a model of the active energy variable with one value drawn from the meter and 3 other hypothetical values, some of which are close to the normal state and some of which are out of the ordinary.

Active import power_{1 (+A)} = 118.6 KW.

Hypo thecal active import power₂ rang = (118.6, 118.3, 118.4) KW (line blue in the (Figure 3.9)).

Hypo thecal active import power₃ rang = (118.6, 100.1, 99,98) KW (line red in the (Figure 3.9)).

Hypo thecal active import power₄ rang = (118.6, 0, 50,50) KW (line yellow in the (Figure 3.9)).

The blue line represents the hypothesis that the effective energy values are in the normal state and that the load has no changes and no unusual events.

The red line in the graph represents the hypothesis that the energy started normally but quickly declined at the end of the hour (as a result of the consumer turning off some of his loads - normal

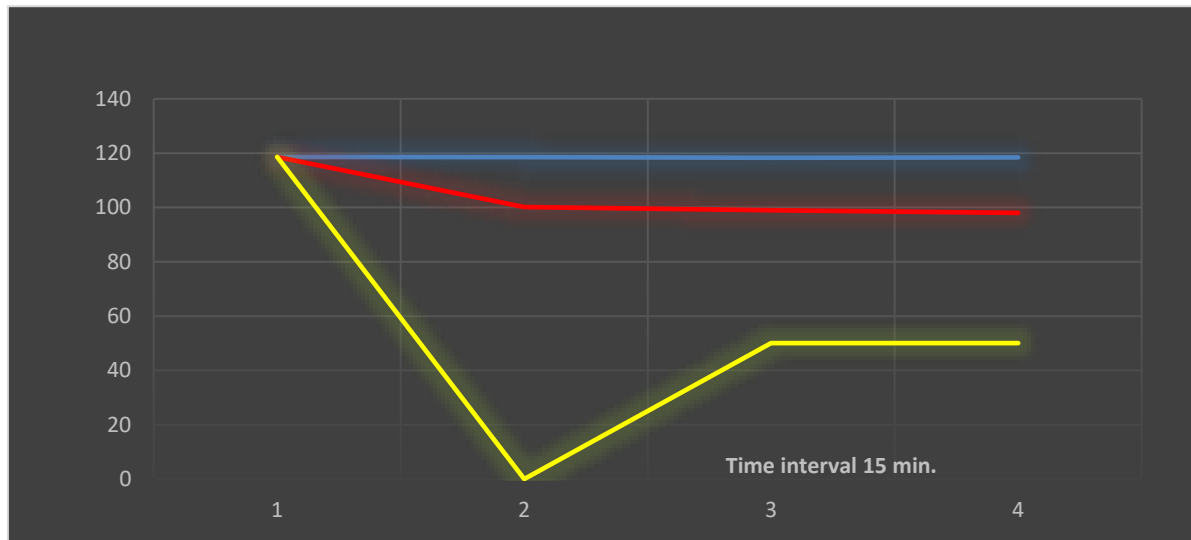


Figure 3.9: Shows the Time Interval 15 Min.

condition - or there is an unusual behaviour - which will be confirmed or denied by the amount of data sent from the smart meter in the coming hours).

The yellow line represents the hypothesis that the energy value started normally and then there was a power outage where the energy reached zero (in conjunction with the current and voltage values in Table 3.4 and Table 3.5) and then returned to the middle value only, and the stability of the situation requires a quick review of the consumer's load to find out whether all loads are within the meter's range or if something abnormal is happening.

b. Detect Non-Technical Losses

The process of determining non-technical loss, or what is known as commercial loss, requires comparing a number of smart meters in different locations. The following line drawing represents a group of smart meters installed in more than one location. Their data sent together must be reviewed at the same time in order to determine the area where the loss occurred.

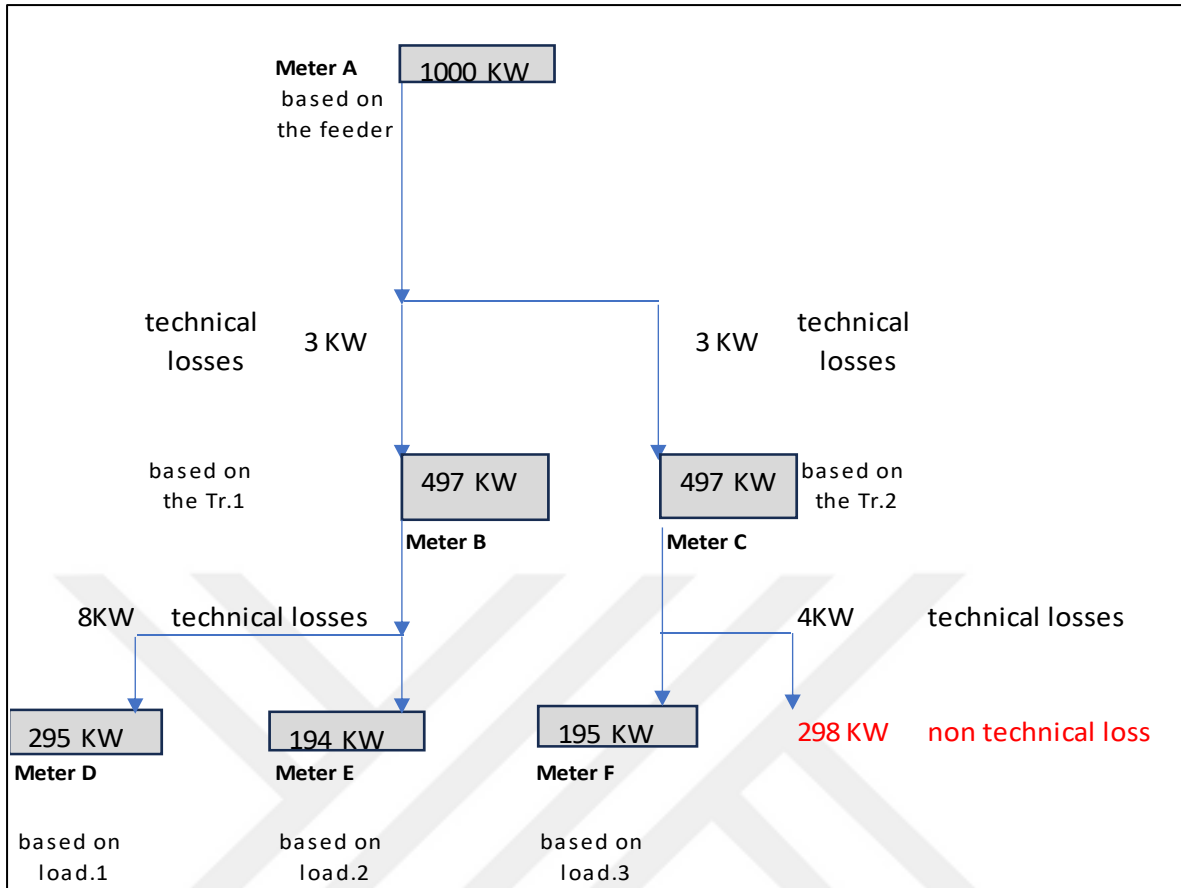


Figure 3.10: Shows Detecting Non-Technical Losses.

(Figure 3.10) shows a simple illustrative concept for the case of detecting non-technical losses, where the server device receives the value of the kW for meters A, B, C, D, E, F at the same time, which shows that the areas in which meters B, C are installed, as well as the areas in which D, E do not have any non-technical losses.

By reviewing the area in which meter F is located, we find that about 298 kW were calculated in meter C and not in meter F. The area is immediately determined and then reviewed technically and legally. The speed of detecting such cases is one of the many advantages of the smart meter, as it maintains the flow of energy and reduces technical and non-technical losses.

2. Load Profiling

The concept of load profile involves tracking the electricity or energy consumption of a building, factory or network over time. It helps in identifying peak consumption periods and

then planning to respond to demand, improve energy efficiency and reduce costs. In light of this definition, we can see that Table 3.8 shows the average demand values, while Table 3.11 shows the instantaneous demand values in the same place. We notice that the average demand value in this area is 90.9 kW Table 3.8 which means that the average consumption of this area in all periods does not exceed 100 kW. This information was of limited benefit to analysts in balancing loads between regions and each other based on averages, while the instantaneous demand value in the same area Table 3.11 is 118.6 kW at 13:43. This takes us to another concept, which is determining peak consumption by recording several instantaneous values, such as Table 3.11 during the day. This enables us to know the daytime peak and the evening peak, when it occurs and how much it is. This is what distinguishes the smart meter from the regular meter.

3. Load Forecasting

We see in [30] some reasons for forecasting load using smart meter data analysis among those reasons:

- a. Identifying customer characteristics and socio-economic data.
- b. Determining the stage.

Load forecasting refers to the prediction of future load. It is widely studied due to its importance in power system planning and operation.

Load forecasting can be divided into four categories [30] as shown in (Figure 3.4).

VSTLF, Short-term load forecasting (STLF), MTLF, And Long-term load forecasting (LTLF).

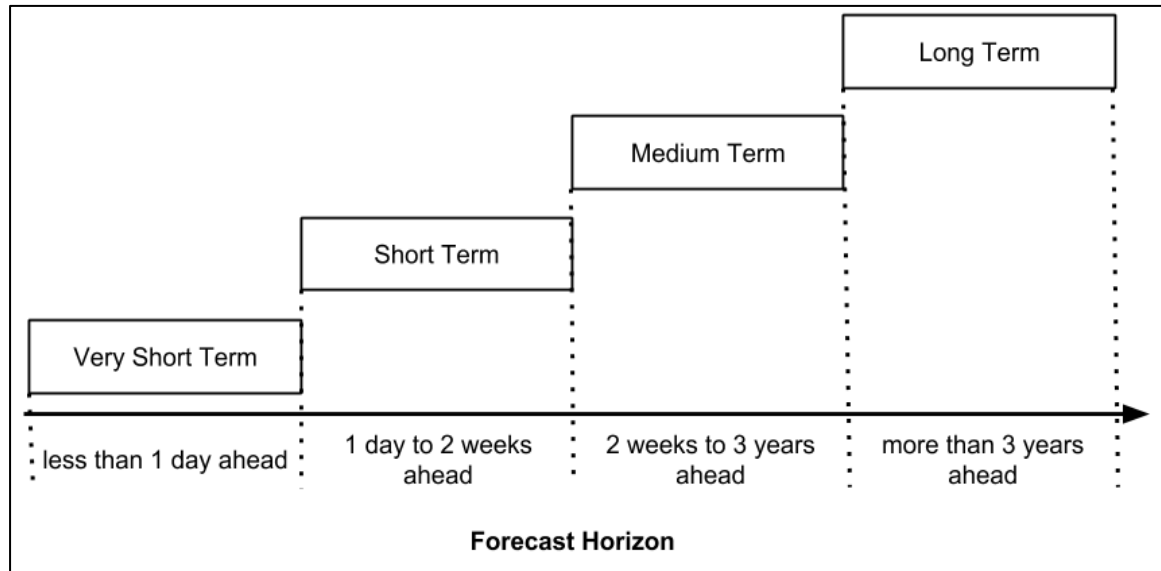


Figure 3.11: Shows the Load Forecasting Categories. [30]

4. Load Forecasting with Individual Meters

Returning to (Figure 3.8), load forecasting using a meter means focusing on a region, institution, or consumer in itself. For example, we saw in the previous example of the load file that the instantaneous value of the load at 13:43 is 118.6 kW, which is higher than the average value 90.9 kW by about 23%, an increase in the short term (where the average value is recorded in the meter during the month, for example), and it was recorded in the middle of the afternoon in August. By linking the climate and temperature data in the Al Khums region in Libya, we find that the direct increase in consumption at this time of day is due to the high temperatures, and if Data for the previous month of August is available. We can predict the percentage increase in the coming August based on the long-term historical file. This is what the smart meter provides with complete accuracy and effectiveness. [32] Key performance indicators (KPIs) are essential for evaluating the accuracy of load forecasting techniques in smart grids. These KPIs help ensure that forecasting is precise, which is crucial for the reliability of electricity systems and avoiding disruptions like blackouts. Here are the main KPIs:

a. Mean Absolute Error (MAE):

$$\text{Error: } e_t = f_t - a_t$$

$$MAE = \frac{1}{n} \sum |e_t| \quad (3.7)$$

b. Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{n} \sum \frac{|e_t|}{a_t} \quad (3.8)$$

c. Root Mean Square Error (RMSE):

$$MSE = \frac{1}{n} \sum e_t^2 \quad (3.9)$$

$$RMSE = \sqrt{\frac{1}{n} \sum e_t^2} \quad (3.10)$$

d. Root Relative Squared Error (RRSE):

$$RRSE = \sqrt{\frac{\sum (f_t - a_t)^2}{\sum (a_t - \bar{a})^2}} \quad (3.11)$$

e. Coefficient of Variation (CV):

CV = RMSE / Mean of actual values

$$CV = \frac{RMSE}{\text{Mean of actual values}} \quad (3.12)$$

Usually KPIs use to evaluate and enhance expected models, secure accurate predictions which help to let the grids stable.

There are two kinds of classification of load forecasting techniques:

1. Parametric Methods

The data is analysed by gathering parameters, so two kinds of methods as below:

a. Regression Method:

Linear Regression: It finds the connected two variables (simple regression) or more than two (multiple regression). It predicts dependent variables according to independent variables.

Multiple Linear Regression: Here, the dependent variable is influenced by multiple independent variables, like weather and other factors that affect electrical load.

b. Time Series Prediction Method:

Autoregressive (AR): This method uses the relationship between current and previous data points in a time series for forecasting.

Moving Average (MA): Forecasting is done based on past white noise or error terms without a linear relationship.

Autoregressive Moving Average (ARMA): A combination of AR and MA models, where the forecast is based on past values and error terms.

Autoregressive Integrated Moving Average (ARIMA): This extends ARMA by adding differencing to make the model suitable for non-stationary time series data.

2. Non-Parametric (AI-based) Methods

These techniques use machine learning and artificial intelligence to model load forecasting and include:

a. ML-based: Various neural network techniques, such as:

ANN, Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and SVM.

b. Rule-based (Fuzzy Logic): Uses fuzzy logic for decision-making processes in load forecasting.

c. Metaheuristic Methods: These involve optimization algorithms such as:

Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO).

d. Hybrid Methods: Combine different AI techniques for improved performance, including:

Deep Learning-based, ANN-based Hybrid, SVM-based Hybrid Advantages, and Disadvantages

e. Parametric methods: These techniques are simpler and based on established statistical relationships. However, they may not perform well in dynamic environments where load is impacted by rapidly changing factors like weather or social conditions.

f. Non-parametric (AI-based) methods: These methods, especially AI-based, are more flexible and can adapt to complex, non-linear relationships. However, they require extensive data and computational power.

Example Applications:

a. Regression Models: Used to forecast short-term load demand (e.g., Borges et al.'s study).

b. Time Series Models (ARIMA): Commonly applied in hourly load forecasting, such as the model by Newsham et al., which used ARIMA for forecasting based on occupancy data.

c. Hybrid Models: Such as Wang et al.'s integration of ARIMA and ANN, which leverages both linear and non-linear relationships for more accurate forecasting.

These techniques are essential for optimizing electricity grid operations and ensuring accurate forecasting for load scheduling, maintenance, and expansion.

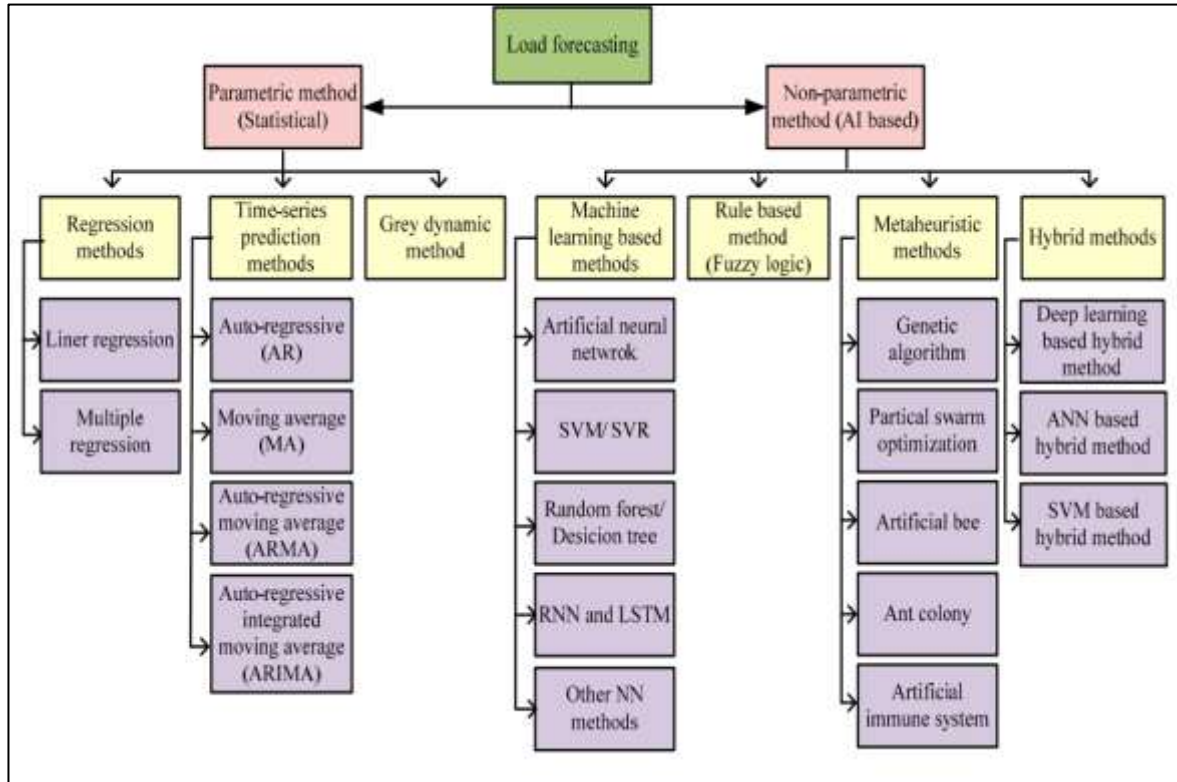


Figure 3.12: Shows the Different Methods Used for Load Forecasting. [32]

5. Load Forecasting Without Individual Meters

One of the simplest and most important concepts of all for predicting the load without a meter is to include future projects, whether in the short or long term. These are clear and well-studied plans, but when implementing, the expected loads from the meters must be taken into account, as we mentioned before, as the percentage increase based on meter data, in addition to the well-studied plans, gives a more accurate prediction of what capacity needs to be added to the network in the future.

a. Probabilistic Forecasting

Probabilistic forecasting is receiving a great deal of attention [30] because it is based on the idea of generating a large number of inputs and feeding them into a prediction model (often a machine learning model that is programmed for this work) and then recording the model outputs to obtain a number of probabilities based on the inputs that were entered from long-term or short-term data.

For example, using temperatures from previous years as inputs and processing them with the corresponding load values that were recorded with these temperatures enables us to obtain more accurate outputs.

b. Load Management

[33] DSM is a key approach to modifying consumers' electricity consumption patterns to reduce the peak load demand, enhance the efficiency of electricity use, and stabilize the power distribution network. It can reduce the need for expanding generation capacity or upgrading transmission and distribution infrastructure. Here's an overview of the DSM techniques and a proposed strategy for their implementation in future smart grids.

Demand Side Management Techniques, DSM techniques are designed to modify load profiles by influencing when and how electricity is consumed. These techniques can broadly be categorized into six methods:

Peak Clipping:

Goal: Reduce the peak electricity demand.

Technique: Direct control of loads during peak times to reduce the demand during those periods. This helps in balancing supply and demand without the need for additional power generation capacity.

Valley Filling:

Goal: Increase load during off-peak periods.

Technique: The technique involves using direct load control to shift some of the demand from peak periods to off-peak periods, thereby utilizing otherwise unused capacity during off-peak times.

Load Shifting:

Goal: Shift demand from peak times to off-peak periods.

Technique: This is one of the most widely used DSM techniques, where flexible loads are moved to non-peak periods. This technique can be achieved through time-of-use tariffs or through automated control systems in smart homes and buildings.

Strategic Conservation:

Goal: Optimize the load shape through demand reduction.

Technique: Conservation strategies can include energy-saving practices or installing more efficient appliances and systems to reduce overall demand.

Strategic Load Growth:

Goal: Manage large increases in demand effectively.

Technique: Focuses on growing the load in a controlled manner, particularly through the use of distributed energy resources (DER) like solar panels or batteries, which help balance the grid by supporting load growth while maintaining system stability.

Flexible Load Shape:

Goal: Enhance the reliability and responsiveness of the grid.

Technique: Identifies customers willing to allow their loads to be controlled during critical periods in exchange for incentives, making the load more flexible and adaptable to grid needs.

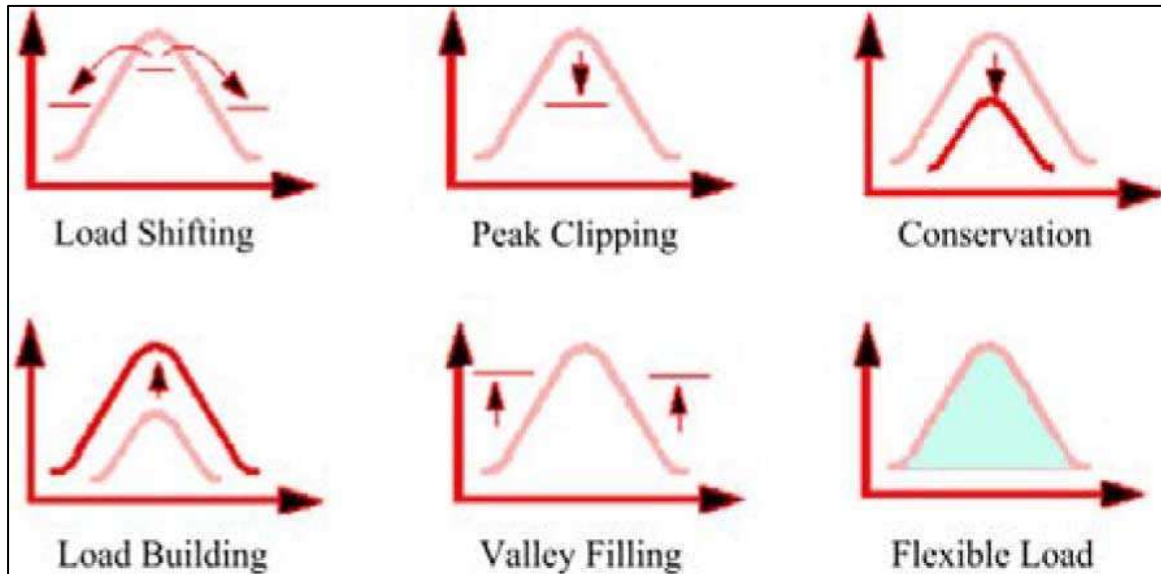


Figure 3.13: Demand Side Management Techniques. [33]

Proposed Demand Side Management Strategy for Smart Grids.

The proposed strategy focuses on load shifting as the main technique for a future smart grid system. The objective of DSM can vary, depending on the specific goal of the utility, such as:

- Maximizing the use of renewable energy (by shifting demand to times when renewable energy sources, like solar or wind, are abundant).
- Minimizing the economic cost (shifting loads when electricity prices are lower, thus reducing the utility bill).
- Reducing peak load demand (shifting or reducing load during peak times to avoid grid congestion and system instability).

In the proposed DSM strategy, the central controller of the smart grid plays a key role. The controller calculates the required load curves and adjusts the consumption patterns to meet the objectives. For instance, if the goal is to reduce utility bills, the load curve would be inversely proportional to electricity market prices, meaning consumption is shifted to periods when electricity is cheapest.

1. Architecture of the DSM Strategy

The architecture for the day-ahead DSM strategy involves the following steps:

a. Objective Load Curve Input: The system receives the target load curve that aligns with the DSM objective (e.g., reducing costs or minimizing peak demand).

b. Optimization Algorithm: The algorithm optimizes the load distribution throughout the day to achieve the objective, by adjusting the load shape to match the desired target.

c. Implementation: Based on the optimization results, smart appliances, smart meters, and other devices can be automatically controlled or provide incentives for customers to participate in DSM programs. This approach helps create a more stable, efficient, and economically feasible power distribution system, particularly in future smart grids, where real-time communication and automation are critical to meeting dynamic energy demands.

In summary, DSM techniques are crucial for managing electricity consumption, reducing peak loads, and integrating renewable energy sources effectively. The proposed strategy utilizing load shifting and optimization algorithms ensures that DSM objectives are met, contributing to grid stability and cost reduction while promoting sustainable energy use.

2. Customer Characteristics

Customer characterization in the context of load management involves segmenting customers based on their usage patterns, behaviours, and other characteristics to create effective load management solutions.

For example:

It is possible to know whether the area is (residential, industrial, or agricultural) by identifying the peak usage. If the peak is in the evening, then the loads are residential. If the peak is during the day, then the loads are industrial. If the peak is every two or three days and is active in certain seasons and not others, then it is most likely agricultural irrigation loads.

a. income levels can be identified (based on affordability).

b. The level of appliances in the home can be identified, whether they have motors, air conditioners, heaters, computers, etc. (based on transient operations, power factor, charge and discharge cycle of compressors and their corresponding surges and surges in current and harmonics in degrees).

3. Commercial and industrial customers can be classified based on:

- a. Business size (small businesses vs. large businesses) of consumption
- b. Operation hours (24/7 operations vs. business hours)
- c. Energy intensive operations (manufacturing plants vs. office buildings)
- d. Current energy saving practices (whether they use energy saving systems or not)

Benefits of combining load management and Customer characteristics:

- a. Pricing and personalized incentives: (such as time-of-use pricing or demand response incentives)
- b. Targeted communication: Energy providers can send targeted messages, to help customers understand how to reduce their energy consumption and benefit from load management programs. Based on all the characteristics mentioned above, here appears the unique advantage of the smart meter system as a whole, which is that it is a system capable of sending and receiving to and from the customer.
- c. Optimal resource allocation: Customer segmentation allows for better planning and resource allocation, ensuring that load management efforts are focused on the most influential customer segments (e.g., high-use areas or industrial customers). The smart meter has succeeded, through the amount of data sent from it, in accurately identifying the target.

3. Demand Response

[31] Demand response programs are demand management techniques that aim to adjust electricity consumption to reduce high peaks in winter and avoid grid improvement costs. These programs are based on adjusting electricity consumption patterns in response to price changes or incentives aimed at encouraging less electricity use at peak times or when system reliability is threatened. The main objectives of demand response are to change electricity consumption through various measures such as improving energy efficiency or shifting the load to other time periods. The methods used include the use of technologies such as cooling, preheating, or storing energy using batteries or thermal storage.

Demand response strategies rely on different levels of automation:

- a. Manual response: requires human intervention to adjust loads.
- b. Semi-automated response: the response is coordinated through central systems and then the schedule is optimized by algorithms.

c. Automated response: the response is activated by external signals, without the need for human intervention.

It is necessary to know the characteristics of the loads and their energy performance to achieve effective implementation of these programs, and this is what the smart system provides based on accurate real-time data.

3.3 COMPARING THE RESULTS

From all of the above, we get the following results, which were based on a real load file from one of the meters in the Libyan city of Al Khums. After simulating and modelling the analysis, if the meter used is a smart meter, we can clearly see Table 3.12. This study compared the performance and benefits of regular meters versus smart meters based on key parameters of data collection, analysis, load forecasting, and management. The comparison highlights the significant advantages of adopting smart meter technology in optimizing energy consumption in Al Khums. Below is a detailed summary of the findings:

Table 3.12: Comparing the Results.

Parameter	Regular Meter	Smart Meters	Advantage of Smart Meters
Data Collection	Collected quarterly, semi-annually, or annually, depending on utility schedules.	Data is collected and transmitted to the server in real-time (every 15 minutes).	Enables real-time monitoring, saves time and effort, minimizes errors, and improves decision-making speed.
Bad Data Detection	Detection is slow, often requiring manual intervention and periodic checks.	Errors can be detected almost instantaneously through automated analysis.	Rapid detection and correction reduce economic losses from inaccurate data or system inefficiencies.

Table 3.12: Comparing the Results “Table Continued”.

Non-Technical Losses	Identification of losses is slow and often requires external auditing or inspections.	Losses (e.g., theft or technical inefficiencies) are identified promptly by analysing data discrepancies.	Enhances energy accountability and reduces financial losses quickly and effectively.
Load Forecasting	Limited to medium-term load forecasting (MTLF).	Enables all forecasting categories: very short-term (VSTLF), short-term (STLF), medium-term (MTLF), and long-term (LTLF).	Provides accurate insights for future load management and network planning, optimizing infrastructure investments.
Load Management	Cannot accurately determine customer characteristics or respond to demand in real-time.	Real-time data enables precise customer segmentation and effective demand response programs.	Facilitates personalized load management solutions and efficient resource allocation.
Customer Empowerment	Offers limited feedback, often delayed, and does not encourage active consumer participation.	Provides real-time feedback on energy consumption patterns, empowering consumers to adjust usage for efficiency.	Encourages energy conservation and supports behavioural changes to reduce peak loads and overall consumption.
Integration of Renewables	Minimal to no integration due to lack of real-time data and limited capacity for two-way communication.	Seamlessly integrates renewable energy sources by providing precise, time-stamped data for grid balancing.	Promotes sustainability and aligns with global energy efficiency and carbon reduction goals.

4. CONCLUSION AND RECOMMENDATIONS

4.1 SUMMARY OF FINDINGS

The analysis of power consumption patterns and the potential implementation of smart meters in Al Khums revealed several key insights. The study shows a huge variation in energy consumption across different times and sides, indicating inefficiencies in the current consumption and billing systems. The adoption of smart meters has demonstrated the potential to achieve accurate and real-time monitoring of electricity consumption, which helps consumers make informed decisions and enables service providers to better manage supply and demand. Furthermore, the integration of smart meter systems can contribute to reducing energy losses, enhancing load management, and improving overall service reliability.

4.2 CONTRIBUTIONS TO KNOWLEDGE

This study clarifies the growing field of energy consumption improvement by providing a specific analysis of a particular area on how to leverage smart meter technologies. It highlights the technical, social, and economic factors that affect energy efficiency in the city of Al Khums, while also supporting a broader understanding of how digital metering systems can lead to more sustainable energy practices. The results provide a valuable framework for policymakers and public utility companies in similar developing regions seeking to modernize their infrastructure.

4.3 RECOMMENDATIONS FOR PRACTICAL IMPLEMENTATION

To make the most of smart meters in Al Khums city, it is proposed to implement the following steps:

- a. Pilot programs: Start pilot projects in selected residential and commercial areas to test the effectiveness of the system and get user feedback.
- b. Public awareness campaigns: Educate consumers on the benefits of smart meters, including energy savings and cost reduction.

- c. Infrastructure Investment: Upgrading the existing electricity grid to support the dual connectivity required to operate smart meters.
- d. Regulatory Support: Doing policies steps that encourage investment in smart grid technologies and ensure data privacy and security.
- e. Incentive programs: Provide financial incentives or financial support to encourage the adoption of smart meters among households and small businesses.

4.4 LIMITATIONS AND FUTURE RESEARCH

Although the study offers promising results, it is not without limitations. The analysis was based on a limited dataset and focused primarily on Al Khums city, which may not fully reflect the reality of other regions that differ in terms of infrastructure and consumption methods, with the long-term impact of smart meter adoption on consumer behavior and network performance still needs to be monitored and monitored.

4.5 FUTURE RESEARCH SHOULD CONSIDER

- a. Conducting broader, multi-regional studies to generalize findings.
- b. Examining the socio-cultural factors affecting user acceptance of smart technologies.
- c. Evaluating the long-term environmental and economic impacts of widespread smart meter implementation.

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APPENDIX A

Data Readout - Current values					
Device identification: ISKT880M90180718					
1	6/8/2024 13:43	0-0:96.1.0*255	*****	unknown	Device ID 1, manufacturing number
2	6/8/2024 13:43	1-0:1.8.0*255	418182042.5	watt hour (Wh)	Active energy import (+A)
3	6/8/2024 13:43	1-0:21.8.0*255	152747059.8	watt hour (Wh)	Active energy import (+A) L1
4	6/8/2024 13:43	1-0:41.8.0*255	139381600.1	watt hour (Wh)	Active energy import (+A) L2
5	6/8/2024 13:43	1-0:61.8.0*255	126053859.4	watt hour (Wh)	Active energy import (+A) L3
6	6/8/2024 13:43	1-0:2.8.0*255	1.5	watt hour (Wh)	Active energy export (-A)
7	6/8/2024 13:43	1-0:22.8.0*255	1.8	watt hour (Wh)	Active energy export (-A) L1
9	6/8/2024 13:43	1-0:62.8.0*255	465.7	watt hour (Wh)	Active energy export (-A) L3
10	6/8/2024 13:43	1-0:3.8.0*255	289355135.8	var hour (varh)	Reactive energy import (+R)
11	6/8/2024 13:43	1-0:23.8.0*255	90176758.4	var hour (varh)	Reactive energy import (+R) L1
12	6/8/2024 13:43	1-0:43.8.0*255	100741939.3	var hour (varh)	Reactive energy import (+R) L2
13	6/8/2024 13:43	1-0:63.8.0*255	98549786.1	var hour (varh)	Reactive energy import (+R) L3
14	6/8/2024 13:43	1-0:4.8.0*255	615404.3	var hour (varh)	Reactive energy export (- R)
15	6/8/2024 13:43	1-0:24.8.0*255	668162.7	var hour (varh)	Reactive energy export (- R) L1
16	6/8/2024 13:43	1-0:44.8.0*255	33616.7	var hour (varh)	Reactive energy export (- R) L2
17	6/8/2024 13:43	1-0:64.8.0*255	26996.6	var hour (varh)	Reactive energy export (- R) L3
18	6/8/2024 13:43	1-0:5.8.0*255	289355133.5	var hour (varh)	Reactive energy QI (+Ri)

19	6/8/2024 13:43	1-0:25.8.0*255	90176744.1	var hour (varh)	Reactive energy QI (+Ri) L1
20	6/8/2024 13:43	1-0:45.8.0*255	100741523.9	var hour (varh)	Reactive energy QI (+Ri) L2
21	6/8/2024 13:43	1-0:65.8.0*255	98548130.8	var hour (varh)	Reactive energy QI (+Ri) L3
22	6/8/2024 13:43	1-0:6.8.0*255	2.2	var hour (varh)	Reactive energy QII (+Rc)
23	6/8/2024 13:43	1-0:26.8.0*255	14.3	var hour (varh)	Reactive energy QII (+Rc) L1
24	6/8/2024 13:43	1-0:46.8.0*255	415.3	var hour (varh)	Reactive energy QII (+Rc) L2
25	6/8/2024 13:43	1-0:66.8.0*255	1655.1	var hour (varh)	Reactive energy QII (+Rc) L3
26	6/8/2024 13:43	1-0:7.8.0*255	0	var hour (varh)	Reactive energy QIII (-Ri)
27	6/8/2024 13:43	1-0:27.8.0*255	1	var hour (varh)	Reactive energy QIII (-Ri) L1
28	6/8/2024 13:43	1-0:47.8.0*255	1.2	var hour (varh)	Reactive energy QIII (-Ri) L2
29	6/8/2024 13:43	1-0:67.8.0*255	4.9	var hour (varh)	Reactive energy QIII (-Ri) L3
30	6/8/2024 13:43	1-0:8.8.0*255	615403.9	var hour (varh)	Reactive energy QIV (-Rc)
31	6/8/2024 13:43	1-0:28.8.0*255	668161.7	var hour (varh)	Reactive energy QIV (-Rc) L1
32	6/8/2024 13:43	1-0:48.8.0*255	33615.2	var hour (varh)	Reactive energy QIV (-Rc) L2
33	6/8/2024 13:43	1-0:68.8.0*255	26991.7	var hour (varh)	Reactive energy QIV (-Rc) L3
34	6/8/2024 13:43	1-0:9.8.0*255	517055598.5	volt-ampere hour (VAh)	Apparent energy import (+VA)
35	6/8/2024 13:43	1-0:29.8.0*255	181149159.7	volt-ampere hour (VAh)	Apparent energy import (+VA) L1
36	6/8/2024 13:43	1-0:49.8.0*255	173854335.1	volt-ampere hour (VAh)	Apparent energy import (+VA) L2
37	6/8/2024 13:43	1-0:69.8.0*255	162054318.8	volt-ampere hour (VAh)	Apparent energy import (+VA) L3

38	6/8/2024 13:43	1-0:10.8.0*255	67.5	volt-ampere hour (VAh)	Apparent energy export (- VA)
39	6/8/2024 13:43	1-0:30.8.0*255	75.2	volt-ampere hour (VAh)	Apparent energy export (- VA) L1
40	6/8/2024 13:43	1-0:50.8.0*255	436.6	volt-ampere hour (VAh)	Apparent energy export (- VA) L2
41	6/8/2024 13:43	1-0:70.8.0*255	1802.7	volt-ampere hour (VAh)	Apparent energy export (- VA) L3
42	6/8/2024 13:43	1-0:15.7.0*255	118572.4	watt (W)	Instantaneous active power combined (+A + - A)
43	6/8/2024 13:43	1-0:1.7.0*255	118572.4	watt (W)	Instantaneous active import power (+A)
44	6/8/2024 13:43	1-0:21.7.0*255	38214.8	watt (W)	Instantaneous active import power (+A) L1
45	6/8/2024 13:43	1-0:41.7.0*255	36133.5	watt (W)	Instantaneous active import power (+A) L2
46	6/8/2024 13:43	1-0:61.7.0*255	44224	watt (W)	Instantaneous active import power (+A) L3
47	6/8/2024 13:43	1-0:2.7.0*255	0	watt (W)	Instantaneous active export power (-A)
48	6/8/2024 13:43	1-0:22.7.0*255	0	watt (W)	Instantaneous active export power (-A) L1
49	6/8/2024 13:43	1-0:42.7.0*255	0	watt (W)	Instantaneous active export power (-A) L2
50	6/8/2024 13:43	1-0:62.7.0*255	0	watt (W)	Instantaneous active export power (-A) L3
51	6/8/2024 13:43	1-0:3.7.0*255	45809.7	var	Instantaneous reactive import power (+R)
52	6/8/2024 13:43	1-0:23.7.0*255	13863	var	Instantaneous reactive import power (+R) L1
53	6/8/2024 13:43	1-0:43.7.0*255	13859.2	var	Instantaneous reactive import power (+R) L2
54	6/8/2024 13:43	1-0:63.7.0*255	18087.4	var	Instantaneous reactive import power (+R) L3
55	6/8/2024 13:43	1-0:4.7.0*255	0	var	Instantaneous reactive export power (-R)

56	6/8/2024 13:43	1-0:24.7.0*255	0	var	Instantaneous reactive export power (-R) L1
57	6/8/2024 13:43	1-0:44.7.0*255	0	var	Instantaneous reactive export power (-R) L2
58	6/8/2024 13:43	1-0:64.7.0*255	0	var	Instantaneous reactive export power (-R) L3
59	6/8/2024 13:43	1-0:5.7.0*255	45809.7	var	Instantaneous reactive power QI (+Ri)
60	6/8/2024 13:43	1-0:25.7.0*255	13863	var	Instantaneous reactive power QI (+Ri) L1
61	6/8/2024 13:43	1-0:45.7.0*255	13859.2	var	Instantaneous reactive power QI (+Ri) L2
62	6/8/2024 13:43	1-0:65.7.0*255	18087.4	var	Instantaneous reactive power QI (+Ri) L3
63	6/8/2024 13:43	1-0:6.7.0*255	0	var	Instantaneous reactive power QII (+Rc)
64	6/8/2024 13:43	1-0:26.7.0*255	0	var	Instantaneous reactive power QII (+Rc) L1
65	6/8/2024 13:43	1-0:46.7.0*255	0	var	Instantaneous reactive power QII (+Rc) L2
66	6/8/2024 13:43	1-0:66.7.0*255	0	var	Instantaneous reactive power QII (+Rc) L3
67	6/8/2024 13:43	1-0:7.7.0*255	0	var	Instantaneous reactive power QIII (-Ri)
68	6/8/2024 13:43	1-0:27.7.0*255	0	var	Instantaneous reactive power QIII (-Ri) L1
69	6/8/2024 13:43	1-0:47.7.0*255	0	var	Instantaneous reactive power QIII (-Ri) L2
70	6/8/2024 13:43	1-0:67.7.0*255	0	var	Instantaneous reactive power QIII (-Ri) L3
71	6/8/2024 13:43	1-0:8.7.0*255	0	var	Instantaneous reactive power QIV (-Rc)
72	6/8/2024 13:43	1-0:28.7.0*255	0	var	Instantaneous reactive power QIV (-Rc) L1
73	6/8/2024 13:43	1-0:48.7.0*255	0	var	Instantaneous reactive power QIV (-Rc) L2
74	6/8/2024 13:43	1-0:68.7.0*255	0	var	Instantaneous reactive power QIV (-Rc) L3

75	6/8/2024 13:43	1-0:9.7.0*255	132158.3	volt-ampere (VA)	Instantaneous apparent import power (+VA)
76	6/8/2024 13:43	1-0:29.7.0*255	42203.6	volt-ampere (VA)	Instantaneous apparent import power (+VA) L1
77	6/8/2024 13:43	1-0:49.7.0*255	40586	volt-ampere (VA)	Instantaneous apparent import power (+VA) L2
78	6/8/2024 13:43	1-0:69.7.0*255	49368.5	volt-ampere (VA)	Instantaneous apparent import power (+VA) L3
79	6/8/2024 13:43	1-0:10.7.0*255	0	volt-ampere (VA)	Instantaneous apparent export power (-VA)
80	6/8/2024 13:43	1-0:30.7.0*255	0	volt-ampere (VA)	Instantaneous apparent export power (-VA) L1
81	6/8/2024 13:43	1-0:50.7.0*255	0	volt-ampere (VA)	Instantaneous apparent export power (-VA) L2
82	6/8/2024 13:43	1-0:70.7.0*255	0	volt-ampere (VA)	Instantaneous apparent export power (-VA) L3
83	6/8/2024 13:43	1-0:14.7.0*255	49.9	hertz (Hz)	Instantaneous net frequency: any phase
84	6/8/2024 13:43	1-0:13.5.0*255	0.885	count	Last average power factor (+A/+VA)
85	6/8/2024 13:43	1-0:13.7.0*255	0.897	count	Instantaneous power factor (+A/+VA)
86	6/8/2024 13:43	1-0:33.5.0*255	0.902	count	Last average power factor (+A/+VA) L1
87	6/8/2024 13:43	1-0:33.7.0*255	0.905	count	Instantaneous power factor (+A/+VA) L1
88	6/8/2024 13:43	1-0:53.5.0*255	0.867	count	Last average power factor (+A/+VA) L2
89	6/8/2024 13:43	1-0:53.7.0*255	0.89	count	Instantaneous power factor (+A/+VA) L2
90	6/8/2024 13:43	1-0:73.5.0*255	0.883	count	Last average power factor (+A/+VA) L3
91	6/8/2024 13:43	1-0:73.7.0*255	0.896	count	Instantaneous power factor (+A/+VA) L3
92	6/8/2024 13:43	1-0:84.5.0*255	0	count	Last average power factor negative (-A/-VA)
93	6/8/2024 13:43	1-0:84.7.0*255	0	count	Instantaneous power factor negative (-A/-VA)

94	6/8/2024 13:43	1-0:85.5.0*255	0	count	Last average power factor negative (-A/-VA) L1
95	6/8/2024 13:43	1-0:85.7.0*255	0	count	Instantaneous power factor negative (-A/-VA) L1
96	6/8/2024 13:43	1-0:86.5.0*255	0	count	Last average power factor negative (-A/-VA) L2
97	6/8/2024 13:43	1-0:86.7.0*255	0	count	Instantaneous power factor negative (-A/-VA) L2
98	6/8/2024 13:43	1-0:87.5.0*255	0	count	Last average power factor negative (-A/-VA) L3
99	6/8/2024 13:43	1-0:87.7.0*255	0	count	Instantaneous power factor negative (-A/-VA) L3
100	6/8/2024 13:43	1-0:31.7.0*255	206	ampere (A)	Instantaneous current L1
101	6/8/2024 13:43	1-0:31.7.124*255	3.1	percent (%)	Instantaneous current L1 THD
102	6/8/2024 13:43	1-0:51.7.0*255	197	ampere (A)	Instantaneous current L2
103	6/8/2024 13:43	1-0:51.7.124*255	11	percent (%)	Instantaneous current L2 THD
104	6/8/2024 13:43	1-0:71.7.0*255	239	ampere (A)	Instantaneous current L3
105	6/8/2024 13:43	1-0:71.7.124*255	0	percent (%)	Instantaneous current L3 THD
106	6/8/2024 13:43	1-0:32.7.0*255	204	volt (V)	Instantaneous voltage L1
107	6/8/2024 13:43	1-0:32.7.124*255	0	percent (%)	Instantaneous voltage L1 THD
108	6/8/2024 13:43	1-0:52.7.0*255	205	volt (V)	Instantaneous voltage L2
109	6/8/2024 13:43	1-0:52.7.124*255	0.9	percent (%)	Instantaneous voltage L2 THD
110	6/8/2024 13:43	1-0:72.7.0*255	206	volt (V)	Instantaneous voltage L3
111	6/8/2024 13:43	1-0:72.7.124*255	1.6	percent (%)	Instantaneous voltage L3 THD
112	6/8/2024 13:43	1-0:1.5.0*255	90922.8	watt (W)	Last average demand register - Active energy import (+A)
113	6/8/2024 13:43	1-0:2.5.0*255	0	watt (W)	Last average demand register - Active energy export (-A)

114	6/8/2024 13:43	1-0:3.5.0*255	44995.2	var	Last average demand register - Reactive energy import (+R)
115	6/8/2024 13:43	1-0:4.5.0*255	0	var	Last average demand register - Reactive energy export (-R)
116	6/8/2024 13:43	1-0:5.5.0*255	44995.2	var	Last average demand register - Reactive energy QI (+Ri)
117	6/8/2024 13:43	1-0:6.5.0*255	0	var	Last average demand register - Reactive energy QII (+Rc)
118	6/8/2024 13:43	1-0:7.5.0*255	0	var	Last average demand register - Reactive energy QIII (-Ri)
119	6/8/2024 13:43	1-0:8.5.0*255	0	var	Last average demand register - Reactive energy QIV (-Rc)
120	6/8/2024 13:43	1-0:9.5.0*255	101872.2	volt-ampere (VA)	Last average demand register - Apparent energy import (+VA)
121	6/8/2024 13:43	1-0:10.5.0*255	0	volt-ampere (VA)	Last average demand register - Apparent energy export (-VA)
122	6/8/2024 13:43	1-0:32.28.0*255	214	volt (V)	Average voltage Time integral 6 L1
123	6/8/2024 13:43	1-0:52.28.0*255	215	volt (V)	Average voltage Time integral 6 L2
124	6/8/2024 13:43	1-0:72.28.0*255	215	volt (V)	Average voltage Time integral 6 L3
125	6/8/2024 13:43	1-0:31.28.0*255	145	ampere (A)	Average current Time integral 6 L1
126	6/8/2024 13:43	1-0:51.28.0*255	138	ampere (A)	Average current Time integral 6 L2
127	6/8/2024 13:43	1-0:71.28.0*255	161	ampere (A)	Average current Time integral 6 L3

APPENDIX B

Graph 1

```
# Import necessary libraries
```

```
import pandas as pd
```

```
import numpy as np
```

```
import matplotlib.pyplot as plt
```

```
import matplotlib.dates as mdates
```

```
# Define the path to the data file
```

```
f
```

```
file_path = "DATA.xlsx" # Ensure the file is in the same working directory or provide the full
```

```
path
```

```
# Read data from the first sheet in the Excel file
```

```
xls = pd.ExcelFile(file_path)
```

```
df = pd.read_excel(xls, sheet_name='Sheet1')
```

```
# Rename columns to organize the data
```

```
df.columns = ["Index", "Timestamp", "Ident", "Value", "Unit", "Description"]
```

```
# Remove unnecessary rows and keep only the data
```

```
df = df.iloc[2:].reset_index(drop=True)
```

```
# Convert the "Timestamp" column to datetime type
```

```
df["Timestamp"] = pd.to_datetime(df["Timestamp"], errors='coerce')
```

```
# Convert the "Value" column to numeric (handling any invalid values)
```

```

df["Value"] = pd.to_numeric(df["Value"], errors='coerce')

# Keep only the data related to energy consumption

df_energy = df[df["Description"].str.contains("Active energy import", na=False)]

# Reshape the data so that each phase is in a separate column

df_energy = df_energy.pivot(index="Timestamp", columns="Description",
values="Value")

# Remove unnecessary columns

df_energy = df_energy.drop(columns=["Last average demand register - Active energy
import
(+A)"], errors='ignore')

# Rename columns for clarity

df_energy.columns = ["Total_Active_Energy (Wh)", "Active_Energy_L1 (Wh)",
"Active_Energy_L2 (Wh)", "Active_Energy_L3 (Wh)"]

# Reset the index

df_energy = df_energy.reset_index()

print(df_energy)

# ----- Simulate Smart Meter Data ----- #

# Set the number of daily readings (96 readings - every 15 minutes)

num_readings = 96

# Create a time array every 15 minutes for 24 hours

time_stamps = pd.date_range(start=df_energy["Timestamp"].iloc[0].replace(hour=0,
minute=0, second=0),
periods=num_readings, freq="15T")

```

```

# Use actual values from the traditional meter as a base for simulation

base_L1 = df_energy["Active_Energy_L1 (Wh)"].iloc[0]

base_L2 = df_energy["Active_Energy_L2 (Wh)"].iloc[0]

base_L3 = df_energy["Active_Energy_L3 (Wh)"].iloc[0]

# Set random variations for each phase using uniform distribution

np.random.seed(42) # Ensure the same random results on each run

random_variation = np.random.uniform(-50000, 50000, (num_readings, 3))

# Calculate energy consumption for each phase throughout the day

simulated_L1 = base_L1 + random_variation[:, 0]

simulated_L2 = base_L2 + random_variation[:, 1]

simulated_L3 = base_L3 + random_variation[:, 2]

# Calculate total energy consumption

simulated_total_energy = simulated_L1 + simulated_L2 + simulated_L3

# Combine data into a DataFrame for the smart meter

smart_meter_data = pd.DataFrame({

    "Timestamp": time_stamps,

    "Active_Energy_L1 (Wh)": simulated_L1,

    "Active_Energy_L2 (Wh)": simulated_L2,

    "Active_Energy_L3 (Wh)": simulated_L3,

    "Total_Active_Energy (Wh)": simulated_total_energy

})

# ----- Plot Comparisons Between Meters ----- #

```

```

# Increase figure size to expand the horizontal axis (e.g., 18 inches instead of 14)

plt.figure(figsize=(24, 6))

# Plot energy consumption from the traditional meter

plt.plot(df_energy["Timestamp"], df_energy["Total_Active_Energy (Wh)"],
label="Traditional Meter - Total Energy", color='r', marker='o', linestyle='dashed',
markersize=8)

# Plot energy consumption from the smart meter

plt.plot(smart_meter_data["Timestamp"], smart_meter_data["Total_Active_Energy
(Wh)"],
label="Smart Meter - Total Energy", color='b', linewidth=2)

# Add titles and labels

plt.xlabel("Time", fontsize=14)

plt.ylabel("Total Active Energy (Wh)", fontsize=14)

plt.title("Comparison Between Traditional and Smart Meter Energy Readings", fontsize=16)

plt.legend(fontsize=12)

plt.grid(True)

# Use date locators to set time intervals every 15 minutes and format them

ax = plt.gca()

ax.xaxis.set_major_locator(mdates.MinuteLocator(interval=15))

ax.xaxis.set_major_formatter(mdates.DateFormatter('%H:%M'))

ax.tick_params(axis='x', labelsz=5) # Increase the size of x-axis labels

plt.xticks(rotation=45)

```

```

# Display the plot

plt.show()

Graph2

# Import necessary libraries

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import matplotlib.dates as mdates

# Define the path to the data file

f

ile_path = "g2.xlsx" # Ensure the file is in the same working directory or provide the full
path

# Read data from the first sheet in the Excel file

xls = pd.ExcelFile(file_path)

df = pd.read_excel(xls, sheet_name='Sheet1')

# Rename columns to organize the data

df.columns = ["Index", "Timestamp", "Ident", "Value", "Unit", "Description"]

# Remove unnecessary rows and keep only the data

df = df.iloc[2:].reset_index(drop=True)

# Convert the "Timestamp" column to datetime type

df["Timestamp"] = pd.to_datetime(df["Timestamp"], errors='coerce')

# Convert the "Value" column to numeric (handling any invalid values)

```

```

df["Value"] = pd.to_numeric(df["Value"], errors='coerce')

# Keep only the data related to energy consumption

df_energy = df[df["Description"].str.contains("Reactive energy import", na=False)]

# Reshape the data so that each phase is in a separate column

df_energy = df_energy.pivot(index="Timestamp", columns="Description",
values="Value")

# Remove unnecessary columns

df_energy = df_energy.drop(columns=["Last average demand register - Reactive energy
import (+A)"], errors='ignore')

# Rename columns for clarity

df_energy.columns = ["Total_Reactive_Energy (Wh)", "Reactive_Energy_L1 (Wh)",
"Reactive_Energy_L2 (Wh)", "Reactive_Energy_L3 (Wh)"]

# Reset the index

df_energy = df_energy.reset_index()

print(df_energy)

# ----- Simulate Smart Meter Data ----- #

# Set the number of daily readings (96 readings - every 15 minutes)

num_readings = 96

# Create a time array every 15 minutes for 24 hours

time_stamps = pd.date_range(start=df_energy["Timestamp"].iloc[0].replace(hour=0,
minute=0, second=0),

periods=num_readings, freq="15T")

```

```

# Use actual values from the traditional meter as a base for simulation

base_L1 = df_energy["Reactive_Energy_L1 (Wh)"].iloc[0]

base_L2 = df_energy["Reactive_Energy_L2 (Wh)"].iloc[0]

base_L3 = df_energy["Reactive_Energy_L3 (Wh)"].iloc[0]

# Set random variations for each phase using uniform distribution

np.random.seed(42) # Ensure the same random results on each run

random_variation = np.random.uniform(-500000, 500000, (num_readings, 3))

# Calculate energy consumption for each phase throughout the day

simulated_L1 = base_L1 + random_variation[:, 0]

simulated_L2 = base_L2 + random_variation[:, 1]

simulated_L3 = base_L3 + random_variation[:, 2]

# Calculate total energy consumption

simulated_total_energy = simulated_L1 + simulated_L2 + simulated_L3

# Combine data into a DataFrame for the smart meter

smart_meter_data = pd.DataFrame({

    "Timestamp": time_stamps,

    "Reactive_Energy_L1 (Wh)": simulated_L1,

    "Reactive_Energy_L2 (Wh)": simulated_L2,

    "Reactive_Energy_L3 (Wh)": simulated_L3,

    "Total_Reactive_Energy (Wh)": simulated_total_energy

})

# ----- Plot Comparisons Between Meters ----- #

```

```

# Increase figure size to expand the horizontal axis (e.g., 18 inches instead of 14)

plt.figure(figsize=(24, 6))

# Plot energy consumption from the traditional meter

plt.plot(df_energy["Timestamp"], df_energy["Total_Reactive_Energy (Wh)"],
label="Traditional Meter - Total Energy", color='r', marker='o', linestyle='dashed',
markersize=8)

# Plot energy consumption from the smart meter

plt.plot(smart_meter_data["Timestamp"], smart_meter_data["Total_Reactive_Energy
(Wh)"],
label="Smart Meter - Total Energy", color='b', linewidth=2)

# Add titles and labels

plt.xlabel("Time", fontsize=14)

plt.ylabel("Total Reactive Energy (Wh)", fontsize=14)

plt.title("Comparison Between Traditional and Smart Meter Energy Readings", fontsize=16)

plt.legend(fontsize=12)

plt.grid(True)

# Use date locators to set time intervals every 15 minutes and format them

ax = plt.gca()

ax.xaxis.set_major_locator(mdates.MinuteLocator(interval=15))

ax.xaxis.set_major_formatter(mdates.DateFormatter('%H:%M'))

ax.tick_params(axis='x', labelsz=5) # Increase the size of x-axis labels

plt.xticks(rotation=45)

```

```

# Display the plot

plt.show()

Graph 3

# Import necessary libraries

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import matplotlib.dates as mdates

# Define the path to the data file

f

file_path = "g3.xlsx" # Ensure the file is in the same working directory or provide the full
path

# Read data from the first sheet in the Excel file

xls = pd.ExcelFile(file_path)

df = pd.read_excel(xls, sheet_name='Sheet1')

# Rename columns to organize the data

df.columns = ["Index", "Timestamp", "Ident", "Value", "Unit", "Description"]

print(df)

# Remove unnecessary rows and keep only the data

# df = df.iloc[2:].reset_index(drop=True)

# print(df)

# Convert the "Timestamp" column to datetime type

```

```

df["Timestamp"] = pd.to_datetime(df["Timestamp"], errors='coerce')

# Convert the "Value" column to numeric (handling any invalid values)

df["Value"] = pd.to_numeric(df["Value"], errors='coerce')

# Keep only the data related to energy consumption

df_energy = df[df["Description"].str.contains("Apparent energy import ", na=False)]

print(df_energy)

# Reshape the data so that each phase is in a separate column

df_energy = df_energy.pivot(index="Timestamp", columns="Description",
values="Value")

print(df_energy)

# Remove unnecessary columns

df_energy = df_energy.drop(columns=["Last average demand register - Apparent energy
import (+A)"], errors='ignore')

print(df_energy)

# Rename columns for clarity

df_energy.columns = ["Total_Apparent_Energy (Wh)", "Apparent_Energy_L1 (Wh)",
"Apparent_Energy_L2 (Wh)", "Apparent_Energy_L3 (Wh)"]

# Reset the index

df_energy = df_energy.reset_index()

print(df_energy)

# ----- Simulate Smart Meter Data ----- #

# Set the number of daily readings (96 readings - every 15 minutes)

```

```

num_readings = 96

# Create a time array every 15 minutes for 24 hours

time_stamps = pd.date_range(start=df_energy["Timestamp"].iloc[0].replace(hour=0,
minute=0, second=0),

periods=num_readings, freq="15T")

# Use actual values from the traditional meter as a base for simulation

base_L1 = df_energy["Apparent_Energy_L1 (Wh)"].iloc[0]

base_L2 = df_energy["Apparent_Energy_L2 (Wh)"].iloc[0]

base_L3 = df_energy["Apparent_Energy_L3 (Wh)"].iloc[0]

# Set random variations for each phase using uniform distribution

np.random.seed(42) # Ensure the same random results on each run

random_variation = np.random.uniform(-5000, 5000, (num_readings, 3))

# Calculate energy consumption for each phase throughout the day

simulated_L1 = base_L1 + random_variation[:, 0]

simulated_L2 = base_L2 + random_variation[:, 1]

simulated_L3 = base_L3 + random_variation[:, 2]

# Calculate total energy consumption

simulated_total_energy = simulated_L1 + simulated_L2 + simulated_L3

# Combine data into a DataFrame for the smart meter

smart_meter_data = pd.DataFrame({

"Timestamp": time_stamps,

"Apparent_Energy_L1 (Wh)": simulated_L1,

```

```

"Apparent_Energy_L2 (Wh)": simulated_L2,

"Apparent_Energy_L3 (Wh)": simulated_L3,

"Total_Apparent_Energy (Wh)": simulated_total_energy

})

# ----- Plot Comparisons Between Meters ----- #

# Increase figure size to expand the horizontal axis (e.g., 18 inches instead of 14)

plt.figure(figsize=(24, 6))

# Plot energy consumption from the traditional meter

plt.plot(df_energy["Timestamp"], df_energy["Total_Apparent_Energy (Wh)"],

label="Traditional Meter - Total Energy", color='r', marker='o', linestyle='dashed',

markersize=8)

# Plot energy consumption from the smart meter

plt.plot(smart_meter_data["Timestamp"], smart_meter_data["Total_Apparent_Energy

(Wh)"],

label="Smart Meter - Total Energy", color='b', linewidth=2)

# Add titles and labels

plt.xlabel("Time", fontsize=14)

plt.ylabel("Total Apparent Energy (Wh)", fontsize=14)

plt.title("Comparison Between Traditional and Smart Meter Energy Readings", fontsize=16)

plt.legend(fontsize=12)

plt.grid(True)

# Use date locators to set time intervals every 15 minutes and format them

```

```

ax = plt.gca()

ax.xaxis.set_major_locator(mdates.MinuteLocator(interval=15))

ax.xaxis.set_major_formatter(mdates.DateFormatter('%H:%M'))

ax.tick_params(axis='x', labelsiz=5) # Increase the size of x-axis labels

plt.xticks(rotation=45)

# Display the plot

plt.show()

graph 4

# Import necessary libraries

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import matplotlib.dates as mdates

# Define the path to the data file

f

ile_path = "g4.xlsx" # Ensure the file is in the same working directory or provide the full
path

# Read data from the first sheet in the Excel file

df = pd.read_excel(file_path, sheet_name='Sheet1')

# Rename columns to organize the data

df.columns = ["Index", "Time", "Ident", "Value", "Unit", "Description"]

# Remove unnecessary rows and keep only the data

```

```

df = df.iloc[2:].reset_index(drop=True)

# Convert the "Time" column to datetime type

df["Time"] = pd.to_datetime(df["Time"], errors='coerce')

# Convert the "Value" column to numeric (handling any invalid values)

df["Value"] = pd.to_numeric(df["Value"], errors='coerce')

# Check for data existence before extraction

def get_value(df, description):

    f

    filtered_data = df[df["Description"].str.contains(description, na=False)]

    if not filtered_data.empty:

        return filtered_data["Value"].values[0]

    else:

        print(f"Warning: No data found for '{description}'")

        return None # Or return a default value like 0

# Extract average and instantaneous voltage data for each phase

average_voltage_L1 = get_value(df, "Average voltage Time integral 6 L1")

average_voltage_L2 = get_value(df, "Average voltage Time integral 6 L2")

average_voltage_L3 = get_value(df, "Average voltage Time integral 6 L3")

instantaneous_voltage_L1 = get_value(df, "Instantaneous voltage L1")

instantaneous_voltage_L2 = get_value(df, "Instantaneous voltage L2")

instantaneous_voltage_L3 = get_value(df, "Instantaneous voltage L3")

```

```

# If any value is missing, use a default value (e.g., 0)

if average_voltage_L1 is None:

    average_voltage_L1 = 0

if average_voltage_L2 is None:

    average_voltage_L2 = 0

if average_voltage_L3 is None:

    average_voltage_L3 = 0

if instantaneous_voltage_L1 is None:

    instantaneous_voltage_L1 = 0

if instantaneous_voltage_L2 is None:

    instantaneous_voltage_L2 = 0

if instantaneous_voltage_L3 is None:

    instantaneous_voltage_L3 = 0

# Calculate total voltage for the traditional meter

total_voltage_traditional = (instantaneous_voltage_L1 + instantaneous_voltage_L2 +

instantaneous_voltage_L3 ) / 3

# ----- Simulate Smart Meter Data ----- #

# Set the number of daily readings (96 readings - every 15 minutes)

num_readings = 96

# Create a time array every 15 minutes for 24 hours

time_stamps = pd.date_range(start=df["Time"].iloc[0].replace(h

```

Graph 5

```

# Import necessary libraries

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import matplotlib.dates as mdates

# Define the path to the data file

f

ile_path = "g5.xlsx" # Ensure the file is in the same working directory or provide the full
path

# Read data from the first sheet in the Excel file

df = pd.read_excel(file_path, sheet_name='Sheet1')

# Rename columns to organize the data

df.columns = ["Index", "Time", "Ident", "Value", "Unit", "Description"]

# Remove unnecessary rows and keep only the data

df = df.iloc[2:].reset_index(drop=True)

# Convert the "Time" column to datetime type

df["Time"] = pd.to_datetime(df["Time"], errors='coerce')

# Convert the "Value" column to numeric (handling any invalid values)

df["Value"] = pd.to_numeric(df["Value"], errors='coerce')

# Check for data existence before extraction

def get_value(df, description):

    filtered_data = df[df["Description"].str.contains(description, na=False)]

```

```

if not filtered_data.empty:

    return filtered_data["Value"].values[0]

else:

    print(f"Warning: No data found for '{description}'")

    return None # Or return a default value like 0

# Extract average and instantaneous current data for each phase

average_current_L1 = get_value(df, "Average current Time integral 6 L1")
average_current_L2 = get_value(df, "Average current Time integral 6 L2")
average_current_L3 = get_value(df, "Average current Time integral 6 L3")

instantaneous_current_L1 = get_value(df, "Instantaneous current L1")
instantaneous_current_L2 = get_value(df, "Instantaneous current L2")
instantaneous_current_L3 = get_value(df, "Instantaneous current L3")

# If any value is missing, use a default value (e.g., 0)

if average_current_L1 is None:

    average_current_L1 = 0

if average_current_L2 is None:

    average_current_L2 = 0

if average_current_L3 is None:

    average_current_L3 = 0

if instantaneous_current_L1 is None:

    instantaneous_current_L1 = 0

if instantaneous_current_L2 is None:

```

```

instantaneous_current_L2 = 0

if instantaneous_current_L3 is None:

instantaneous_current_L3 = 0

# Calculate total current for the traditional meter

total_current_traditional = (instantaneous_current_L1 + instantaneous_current_L2 +

instantaneous_current_L3) / 3

# ----- Simulate Smart Meter Data ----- #

# Set the number of daily readings (96 readings - every 15 minutes)

num_readings = 96

# Create a time array every 15 minutes for 24 hours

time_stamps = pd.date_range(start=df["Time"].iloc[0].replace(hour=0, minute=0,

second=0),

periods=num_readings, freq="15T")

# Simulate current readings for the smart meter for each phase

np.random.seed(42) # Ensure the same random results on each run

# Add small random variations to the current

random_variation_L1 = np.random.uniform(-5, 5, num_readings) # Change the range to ±5
A

random_variation_L2 = np.random.uniform(-5, 5, num_readings)

random_variation_L3 = np.random.uniform(-5, 5, num_readings)

# Calculate simulated readings for each phase

simulated_current_L1 = instantaneous_current_L1 + random_variation_L1

```

```

simulated_current_L2 = instantaneous_current_L2 + random_variation_L2

simulated_current_L3 = instantaneous_current_L3 + random_variation_L3

# Calculate total current for the smart meter

simulated_total_current = (simulated_current_L1 + simulated_current_L2 +
simulated_current_L3) / 3

# Combine data into a DataFrame for the smart meter

smart_meter_data = pd.DataFrame({

"Timestamp": time_stamps,

"Current_L1 (A)": simulated_current_L1,

"Current_L2 (A)": simulated_current_L2,

"Current_L3 (A)": simulated_current_L3,

"Total_Current (A)": simulated_total_current

})

# ----- Plot Comparisons Between Meters ----- #

# Increase figure size to expand the horizontal axis

plt.figure(figsize=(24, 6))

# Plot total current from the traditional meter as a single point

plt.scatter(df["Time"].iloc[0], total_current_traditional, color='r', s=100, label="Traditional

Meter - Average Current")

# Plot total current from the smart meter (reading every 15 minutes)

plt.plot(smart_meter_data["Timestamp"], smart_meter_data["Total_Current (A)"],

label="Smart Meter - Average Current", color='b', linewidth=2)

```

```

# Add titles and labels

plt.xlabel("Time", fontsize=14)

plt.ylabel("Average Current (A)", fontsize=14)

plt.title("Comparison Between Traditional and Smart Meter Average Current Readings",
          fontsize=16)

plt.legend(fontsize=12)

plt.grid(True)

# Use date locators to set time intervals every 15 minutes and format them

ax = plt.gca()

ax.xaxis.set_major_locator(mdates.MinuteLocator(interval=15))

ax.xaxis.set_major_formatter(mdates.DateFormatter('%H:%M'))

ax.tick_params(axis='x', labelsize=5) # Increase the size of x-axis labels

plt.xticks(rotation=45)

# Display the plot

plt.show()

```

Graph 6

```

# Import necessary libraries

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

import matplotlib.dates as mdates

# Define the path to the data file

```

f

```
ile_path = "g6.xlsx" # Ensure the file is in the same working directory or provide the full path
```

```
# Read data from the first sheet in the Excel file
```

```
df = pd.read_excel(file_path, sheet_name='Sheet1')
```

```
# Rename columns to organize the data
```

```
df.columns = ["Index", "Time", "Ident", "Value", "Unit", "Description"]
```

```
# Remove unnecessary rows and keep only the data
```

```
# df = df.iloc[2:].reset_index(drop=True)
```

```
# Convert the "Time" column to datetime type
```

```
df["Time"] = pd.to_datetime(df["Time"], errors='coerce')
```

```
# Convert the "Value" column to numeric (handling any invalid values)
```

```
df["Value"] = pd.to_numeric(df["Value"], errors='coerce')
```

```
# Check for data existence before extraction
```

```
def get_value(df, description):
```

```
    filtered_data = df[df["Description"].str.contains(description, na=False)]
```

```
    if not filtered_data.empty:
```

```
        return filtered_data["Value"].values[0]
```

```
    else:
```

```
        print(f"Warning: No data found for '{description}'")
```

```
    return None # Or return a default value like 0
```

```

# Extract instantaneous frequency data

instantaneous_frequency = get_value(df, "Instantaneous net frequency")

# If the value is missing, use a default value (e.g., 0)

if instantaneous_frequency is None:

    instantaneous_frequency = 0

# ----- Simulate Smart Meter Data ----- #

# Set the number of daily readings (96 readings - every 15 minutes)

num_readings = 96

# Create a time array every 15 minutes for 24 hours

time_stamps = pd.date_range(start=df["Time"].iloc[0].replace(hour=0, minute=0,
second=0),

                             periods=num_readings, freq="15T")

# Simulate frequency readings for the smart meter

np.random.seed(42) # Ensure the same random results on each run

# Add small random variations to the frequency

random_variation = np.random.uniform(-0.1, 0.1, num_readings) # Change the range to
±0.1 Hz

# Calculate simulated readings

simulated_frequency = instantaneous_frequency + random_variation

# Combine data into a DataFrame for the smart meter

smart_meter_data = pd.DataFrame({

    "Timestamp": time_stamps,

```

```

"Frequency (Hz)": simulated_frequency

})

# ----- Plot Comparisons Between Meters ----- #

# Increase figure size to expand the horizontal axis

plt.figure(figsize=(24, 6))

# Plot frequency from the traditional meter as a single point

plt.scatter(df["Time"].iloc[0], instantaneous_frequency, color='r', s=100, label="Traditional

Meter - Frequency")

# Plot frequency from the smart meter (reading every 15 minutes)

plt.plot(smart_meter_data["Timestamp"], smart_meter_data["Frequency (Hz)"],

label="Smart Meter - Frequency", color='b', linewidth=2)

# Add titles and labels

plt.xlabel("Time", fontsize=14)

plt.ylabel("Frequency (Hz)", fontsize=14)

plt.title("Comparison Between Traditional and Smart Meter Frequency Readings",

fontsize=16)

plt.legend(fontsize=12)

plt.grid(True)

# Use date locators to set time intervals every 15 minutes and format them

ax = plt.gca()

ax.xaxis.set_major_locator(mdates.MinuteLocator(interval=15))

ax.xaxis.set_major_formatter(mdates.DateFormatter('%H:%M'))

```

```
ax.tick_params(axis='x', labelsiz=5) # Increase the size of x-axis labels  
  
plt.xticks(rotation=45)  
  
# Display the plot  
  
plt.show()
```

