# Deep Neural Network-Based Optimisation for Clustered Demand-Side Energy Management in Smart Grids

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# Abstract

This thesis conducts an in-depth investigation into the optimisation of Clustered Demand-Side Energy Management (CDEM) in smart grids through a Deep Neural Network (DNN)-based methodology. The study emphasises the strategic clustering of consumers and prosumers based on their energy consumption and generation profiles. By leveraging DNNs, the framework aims to accurately forecast energy demand, regulate load distribution, and support real-time optimisation objectives. The integration of Advanced Metering Infrastructure (AMI) and Internet of Things (IoT)-enabled devices underpins the data acquisition process, enabling precise clustering and dynamic energy management that is responsive to diverse user consumption behaviours.

The proposed architecture incorporates K-means clustering to group energy users according to their usage patterns. To enhance clustering performance, the study applies feature engineering techniques such as data scaling, correlation analysis, and comprehensive preprocessing. These measures contribute to more effective deployment of demand response strategies, ultimately reducing simultaneous peak demand and enhancing the operational stability of the smart grid. The DNN model is employed for high-fidelity prediction of energy usage and real-time demand response management. Its efficacy is validated through multiple performance metrics, including regression plots, confusion matrices, and error histograms, all of which reflect low prediction error, high classification accuracy, and consistent reliability across varied test cases. Real-world datasets obtained from smart meters further validate the model, offering granular insights into consumer energy usage dynamics.

Additionally, the research investigates voltage and frequency regulation using DNNs, comparing their performance to conventional PID controllers. The outcomes highlight the DNN model's superior accuracy and faster responsiveness in stabilizing grid operations. This thesis also explores fault and fraud detection mechanisms, applying DNNs to identify deviations in energy consumption patterns. The developed fault detection algorithms show notable improvements in detecting both supply-side and load-side anomalies. These algorithms are validated through Receiver Operating

Characteristic (ROC) curve analysis, which measures the trade-off between true and false positives, and ensemble methods, further enhancing detection accuracy.

Linking to the clustered energy management framework, the research integrates renewable energy sources (RES) like wind and solar into these clusters, enabling optimisation of both conventional and renewable systems. Several case studies involving residential solar-powered systems and hybrid commercial loads have been implemented to evaluate the effectiveness of net-zero energy management strategies. These case studies highlight the critical role of battery energy storage systems (BESS) and demand response mechanisms in achieving optimal energy utilisation. The findings demonstrate the practical applicability of the proposed framework in diverse operational contexts, reinforcing its capability to support net-zero objectives through coordinated control of distributed energy resources. The results indicate significant improvements around 99.50% in energy efficiency and system reliability compared to traditional approaches, reducing energy waste and enhancing grid stability. Finally, the research provides key insights for future smart grid optimisation, emphasising the role of advanced AI techniques, such as DNNs, in advancing sustainable and resilient energy systems.

The key contributions of this research are as follows:

1. **Novel Framework Design:** Introducing a clustered-based DNN framework tailored for CDEM in smart grids.
2. **DNN Implementations:** Establishing the advantage of DNNs in handling large-scale, dynamic energy datasets through deeper architectures and enhanced learning capabilities.
3. **Enhanced Energy Management:** Demonstrating the effectiveness of clustering to capture consumer-specific energy usage patterns and optimize demand-side strategies.
4. **Comprehensive Comparisons:** Providing a detailed analysis of the proposed approach against existing methods, emphasizing its scalability, adaptability, and superior performance.

This work significantly advances smart grid technology, offering valuable insights for developing sustainable and efficient energy management systems. The findings underline the potential of DNN-based clustered frameworks to drive future innovations in the pursuit of net-zero energy goals.

# Acknowledgement

I am profoundly grateful to my principal supervisor, Dr. Alison Griffiths, for her exceptional guidance, constructive feedback, and steadfast support throughout my PhD journey. Her expertise and encouragement have been instrumental in the completion of my research on "Deep Neural Network-Based Optimisation for Clustered Demand-Side Energy Management in Smart Grids" at University of Staffordshire.

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My heartfelt gratefulness goes on to my parents and family, whose endless love, encouragement, and sacrifices have been my greatest strength. Their confidence in me has been a constant source of motivation. Special thanks to my brothers Aftab Hameed and Faheem Akram, whose support and camaraderie have made this journey more enjoyable and fulfilling.

During these four years, I had the opportunity to gain valuable experience as a part-time lecturer and technical specialist. Additionally, my role as a student ambassador allowed me to engage in numerous events, seminars, and conferences, enriching my academic and professional life. One of my proudest achievements during this period was attaining the AFHEA fellowship, which recognized my commitment to teaching and learning.

Thank you to everyone who has contributed to this significant milestone in my academic career.

# Author's Declaration

I, **Zia Hameed**, hereby declare that the work presented in this thesis entitled **"Deep Neural Network-Based Optimisation for Clustered Demand-Side Energy Management in Smart Grids"** is the result of my own research. This thesis has not been submitted, either fully or partially, for any qualification or degree at University of Staffordshire or any other institution.

In contributing to the existing knowledge on smart grids and energy management, I have developed an innovative approach that leverages a Deep Neural Network (DNN) to optimise clustered demand-side energy management. My research involves developing an innovative framework to generate load profiles for different consumer clusters. This will empower utility companies and customers alike to monitor and supervise energy consumption in real-time, enhancing efficiency and enabling better decision-making around energy use. By providing insights into consumption patterns, this framework aims to facilitate more effective energy management strategies for both utilities and consumers. I confirm that all aspects of this work, including the plan, methodology, and completion of the intended system are original to this thesis. There has been no collaboration in the creation of this work.

I understand that failure to comply with these guidelines constitutes academic misconduct.

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# List of Acronyms

| | |
|---|---|
| AI | Artificial Intelligence |
| CI | Computational Intelligence |
| CDEM | Clustered Demand-Side Energy Management |
| DNN | Deep Neural Network |
| DSEM | Demand side energy management |
| DR | Demand Response |
| DG | Distributed Generation |
| DSR | Demand-Side Response |
| EMS | Energy Management System |
| ESS | Energy Storage System |
| EMC | Electromagnetic Compatibility |
| EMI | Electromagnetic Interface |
| GE | Genetic Algorithm |
| HAN | Home Area Network |
| IOT | Internet of Things |
| ML | Machine Learning |
| MAE | Mean Absolute error |
| MSE | Mean Squared Error |
| PMU | Phasor Measurement Unit |
| PSO | Particle Swarm Optimization |
| PID | Proportional – Integral – Derivative |
| ROC | Receiver Operating Characteristics |
| RES | Renewable Energy Resources |
| SG | Smart Grid |
| SOC | State of Charge |
| SCADA | Supervisory Control and Data Acquisition |
| VM | Virtual Machine |

# Chapter 1: Introduction to Smart Grids and Demand Side Energy Management

Electricity is an imperative part of modern life that's why the global escalation of energy demand requires a system which efficiently fulfils the need of all consumers (Halder and Pervez 2015). The electricity grid infrastructure is more than 50 years old, even in the most developed countries it is estimated both by industries and academia that, to address the insufficient energy issues all will have to move to a smart grid philosophy (Easther-2016, Haider-2016). A smart grid utilizes modern controls, communication and sensing technologies which can assist in accomplishing the growing energy needs of by utilizing appropriate management techniques (Gungor et al. 2011).

The traditional grid system is centralized, where energy is transferred from a main source to the end user via various transmission and distribution networks. This requires maintenance of all the systems involved and technical losses due to long distance between generation point to consumer side is of major concern (Ackermann et al. 2001). The execution of the electricity network highly depends upon the balance between energy production and consumer's demand. Moreover, the quantity of energy consumed has its effect on the distribution system which makes the grid system unreliable. To ensure grid reliability and to meet the escalated energy demand, distributed generation through Renewable Energy Sources (RES) and Energy Storage System (ESS) needs to be considered. According to the viewpoint of small and medium sized customers, electricity is being used in an unintelligent and uncontrolled way, these two factors make the energy increasingly expensive (Lasseter 2002; Gellings 2017).

DSEM consists of load management techniques for planning, execution and monitoring of pre-planned actions which also creates an influence on consumer's energy usage pattern (Ding et al. 2016). By using DSEM techniques, the available energy can be systematically transmitted and distributed to overcome the peak load demands and allow customers to select their choice of energy source (Maharjan 2014). The implementation of demand response (DR) approaches allows the automatic real-time interaction between generators and tasks to switch the user's energy requirements at peak times. Advanced approaches of DR will be able to control DSEM which are beneficial to increase the equipment's life as well as it is valuable for the economics of any country.

There are six types of Demand Response approaches for DSEM from peak clipping to flexible load shifting, which are shown in Figure 1-1 (Dileep 2020). Currently, the communication levels of the SG are growing with the control of high-value devices, such as generating installations, transmission lines, workstations, and large energy users.

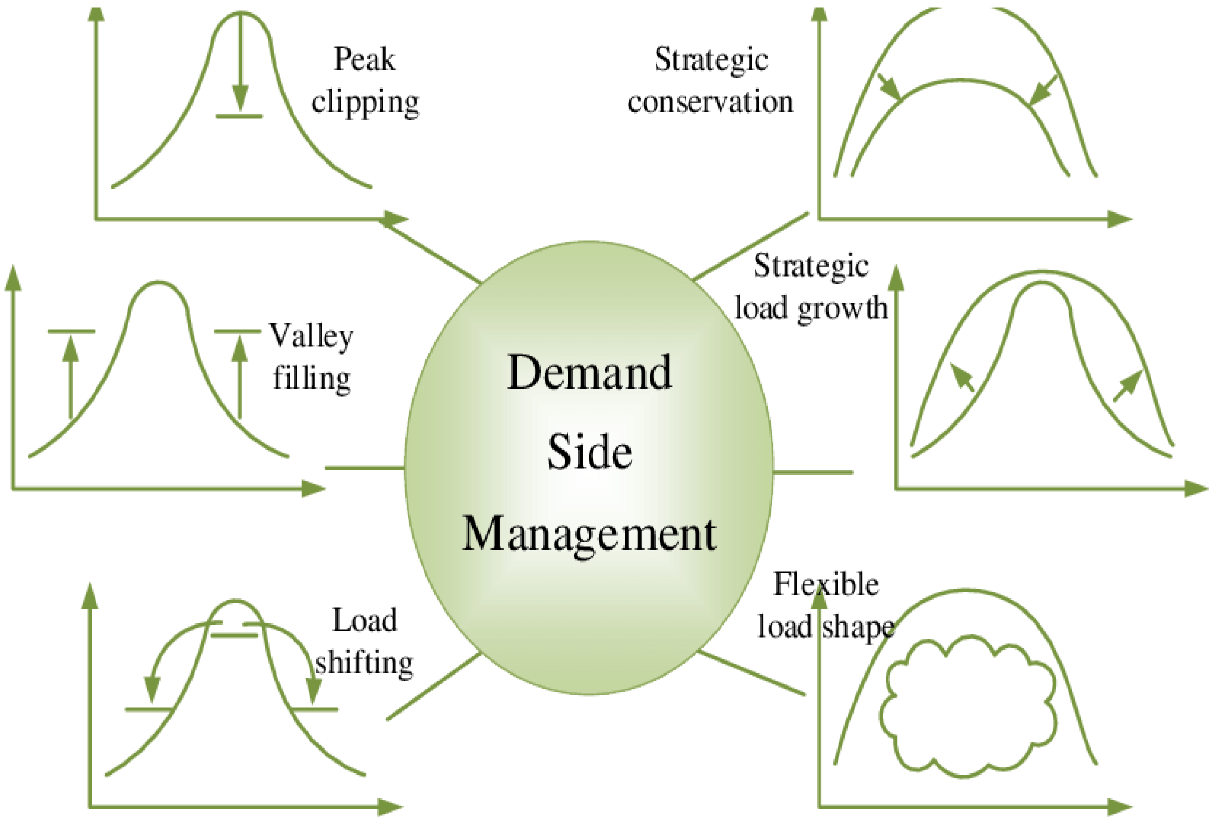



Figure 1-1: Various approaches for DSEM in SG (Dileep 2020)

Neural networks can be used for smart meter data monitoring to provide insights into energy usage patterns, identify anomalies, and enable predictive maintenance. Smart meters generate large amounts of data that can be difficult to process and analyse, but neural networks are well suited for handling large amounts of data and identifying patterns and trends (Mufana, Ibrahim, 2022).

Neural networks can be used for smart meter data monitoring for different perspectives as follows:

1. **Load forecasting:** Neural networks can be used to predict future energy consumption based on historical usage patterns. This can help utility

companies to anticipate future demand and optimise their energy generation and distribution.

2. **Anomaly detection:** Neural networks can be used to identify unusual or abnormal energy consumption patterns, which could indicate equipment malfunctions or fraud. This can help to prevent equipment failures and reduce the risk of energy theft.
3. **Predictive maintenance:** Neural networks can be used to analyse historical data to predict when equipment may fail or require maintenance. This can help to reduce downtime and maintenance costs and improve overall system reliability.
4. **Demand response:** Neural networks can be used to identify peak demand periods and incentivize consumers to reduce their energy usage during these periods. This can help to reduce strain on the energy grid during times of high demand.

To implement neural network-based smart meter data monitoring, utility companies typically use specialized software platforms that are capable of processing large volumes of data in real-time. These platforms use algorithms and machine learning techniques to analyse the data and provide insights into energy usage patterns, anomalies, and potential issues such as equipment failures or theft (LJ Lepolesa, S Achari, 2022).

Neural networks offer a powerful solution for monitoring smart meter data, delivering insights into energy consumption patterns and facilitating predictive maintenance and demand response. By harnessing machine learning, they can help lower energy costs, enhance system reliability, and support sustainable energy methods.

The role of smart meter data collection is fundamental in establishing a smart grid, an advanced power system that employs digital communication technology to oversee and improve electricity generation, transmission, and distribution. Smart meters track energy consumption almost in real-time, relaying this data to utility companies.

**For utility providers, smart meter data collection provides several benefits, such as:**

1. Improved grid management: By collecting data on energy consumption patterns, utilities can better manage the grid and optimise its performance. They can use the data to identify areas of high demand and accommodate supply accordingly, which can help prevent blackouts and brownouts.

2. More accurate billing: Smart meters provide more accurate and timely data on energy usage, which can lead to more accurate billing and fewer disputes between customers and utilities.
3. Better customer service: Smart meters can help utilities identify issues with individual customer accounts more quickly, leading to faster resolution of billing issues and other problems.

**For consumers, smart meter data collection provides several benefits, such as:**

1. Better understanding of energy usage: Smart meters provide detailed information on energy usage, which can help consumers identify ways to reduce their energy consumption and lower their bills.
2. More control over energy usage: With real-time data on energy usage, consumers can make informed decisions about when to use energy-intensive appliances and when to reduce their energy consumption.
3. More accurate billing: Smart meters provide more accurate data on energy usage, which can help ensure that consumers are billed correctly.

Consumers who also produce their own electricity through renewable sources like solar and wind energy are known as prosumers. Smart meter data collection is essential for gathering information on both consumers and prosumers. Through smart meters, prosumers can monitor their energy production and consumption, helping them enhance their renewable systems and transfer any excess energy to the grid.

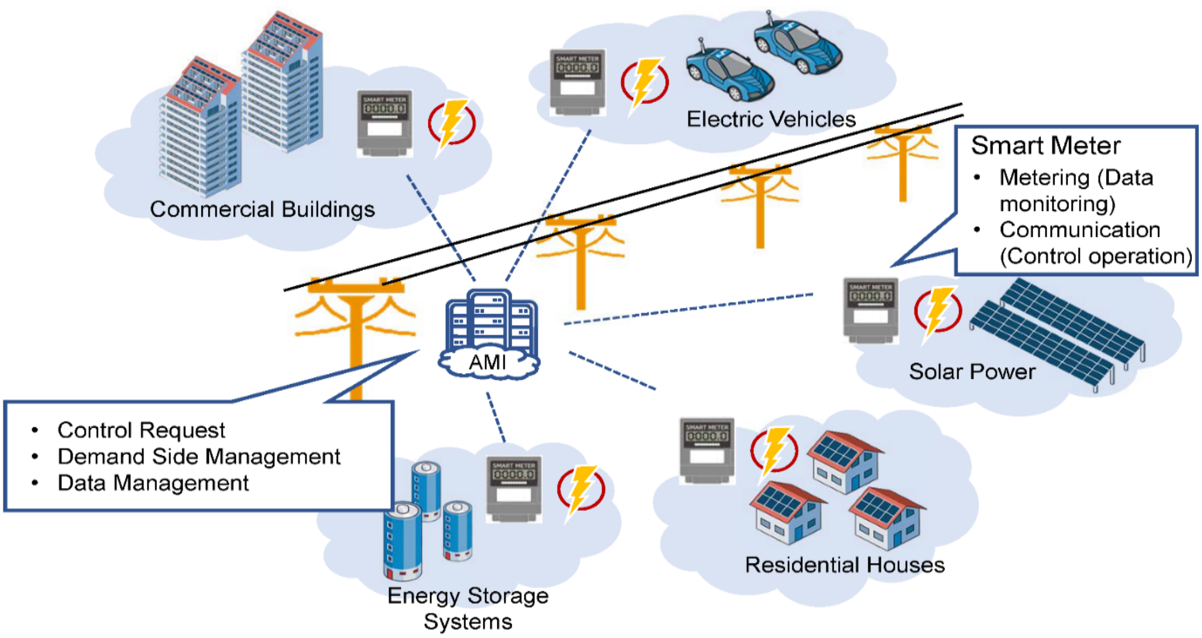



Figure 1-2: Advanced Metering Infrastructure in Smart Grid (Smolenski, 2022)

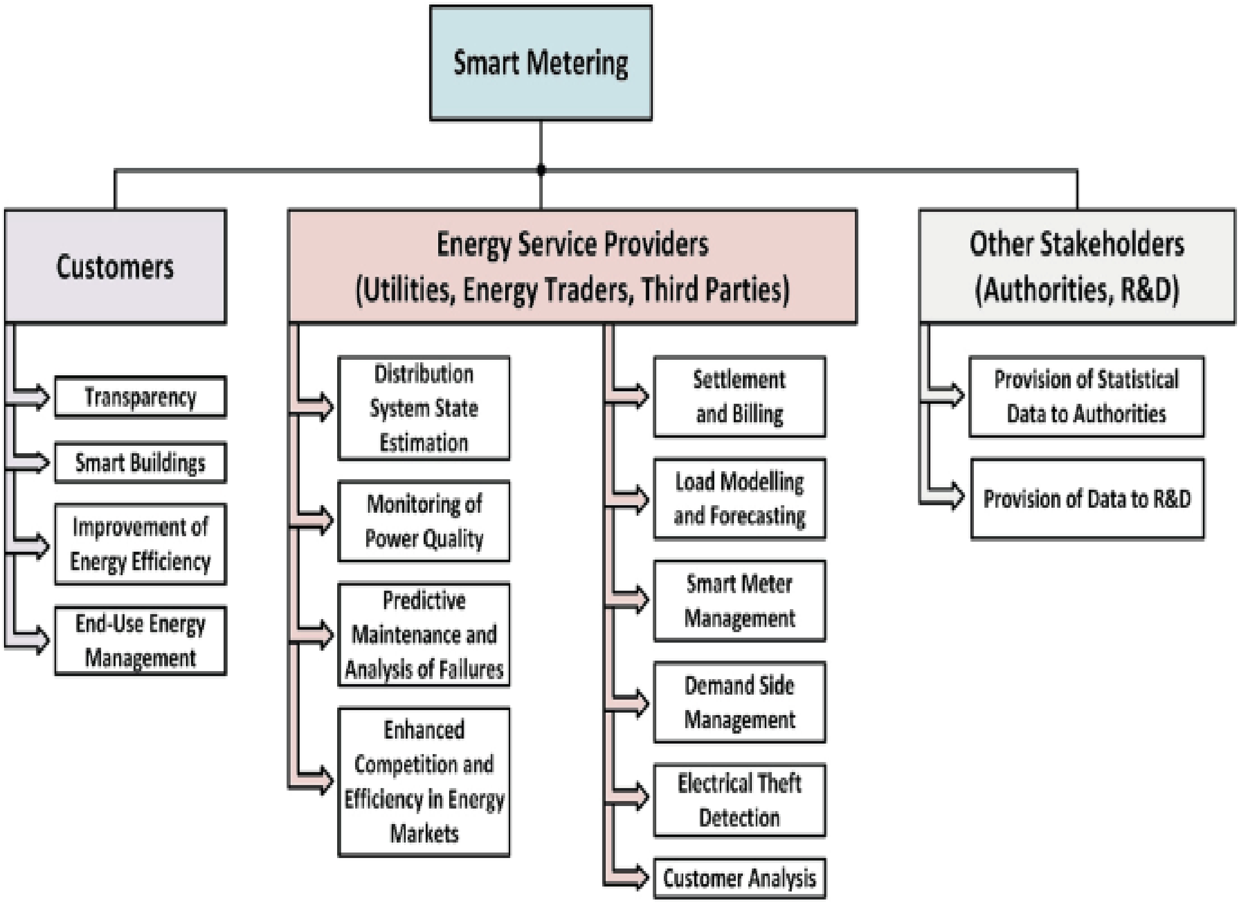



Figure 1-3: Benefits of Smart Metering (Shokry, Awad, 2022)

Overall, smart meter data collection is a key component of a smart grid, providing benefits to electricity providers, consumers, and prosumers alike. Overall, concept of advance metering infrastructure in SG and it's benefits are shown in Figure 1-2 and Figure 1-3 respectively.

The two way energy flow, towards and from the grid by a prosumer can be measured in nearly real-time using a smart meter, this enables providers and prosumers to be more responsive instead of consumers for real-time energy demands (Savani 2018), this results in a more efficient as compared to a one-way energy flow. The one-line flow of energy and information is costly as compared to this proposed system, resulting it is difficult and complex to control DSEM and optimise the energy system. The IoT-based smart apparatuses can be installed and integrated practically in SG infrastructure. According to a recent survey report, energy demand is presumed to rise significantly in the coming years, with global industrial energy consumption projected to reach approximately 315 quadrillion British thermal units (Btu) by 2050, (Anoune et al. 2018). The public safety, public economy, and the medical services of the consumers dynamically depends on the stable and consistent circulation of power (Koutroulis et al.2006). The infrastructure of traditional power grid is static with high response time and is inefficient to solve the requests of customers. SG have an advanced infrastructure of energy and communication which is beneficial to change the method of creation, dissemination, and control of power in efficient way (Koutroulis 2010; Zeng 2010). Cutting-edge technology is the advancement that refers to the advance techniques and approaches implementation in SG will lead to consumers being able to manage their own requirements in real-time dynamically, this will be facilitated by using a smart framework practically. SG is the combined form of efficient smart networks from providers to consumer end by integrating RES to meet the concept of zero-energy. Advance countries around the globe have begun to adopt a smart network approach in electrical systems, as a result the electricity providers are starting to implement this approach for the benefits of their consumers (Amer 2013; Ghofrani 2016).

The SG designing involves the billions of smart apparatuses, efficient meters, smart sensors, etc. alongside various correspondence advance arrangements whether private or public (Li et al. 2014).

However, the security challenges applying Artificial Intelligence (AI) are investigated on the ML and IOT implementation in SG. The AI role in advance areas including the SG is shown in Figure 1-4. The process protected the versatile DSEM by utilizing the ML approaches to defeat the security issue in the SG. The proposed DSEM is checked by implementing the ML classifier such as DNN to optimise the entire network more efficiently in a secure way and it is possible to control the DSEM of SG at each cluster and consumer's side. A particular Home Area Network (HAN) is assigned to understand the proposed DSEM by implementing DNN (Hakimi et al. 2009). DNN is ultimately human brain modeling with multiple inputs, hidden and output layers' structural configuration. DNN brain working is same as human brain with thousands of parallel processing tasks are working side by side with fully efficient and secure way to enhance the capacity of DSEM in SG (Lee et al. 2009). The overall benefits of DSM is shown in Figure 1-5, in aspects of economically, technically, environmentally, and marketable.

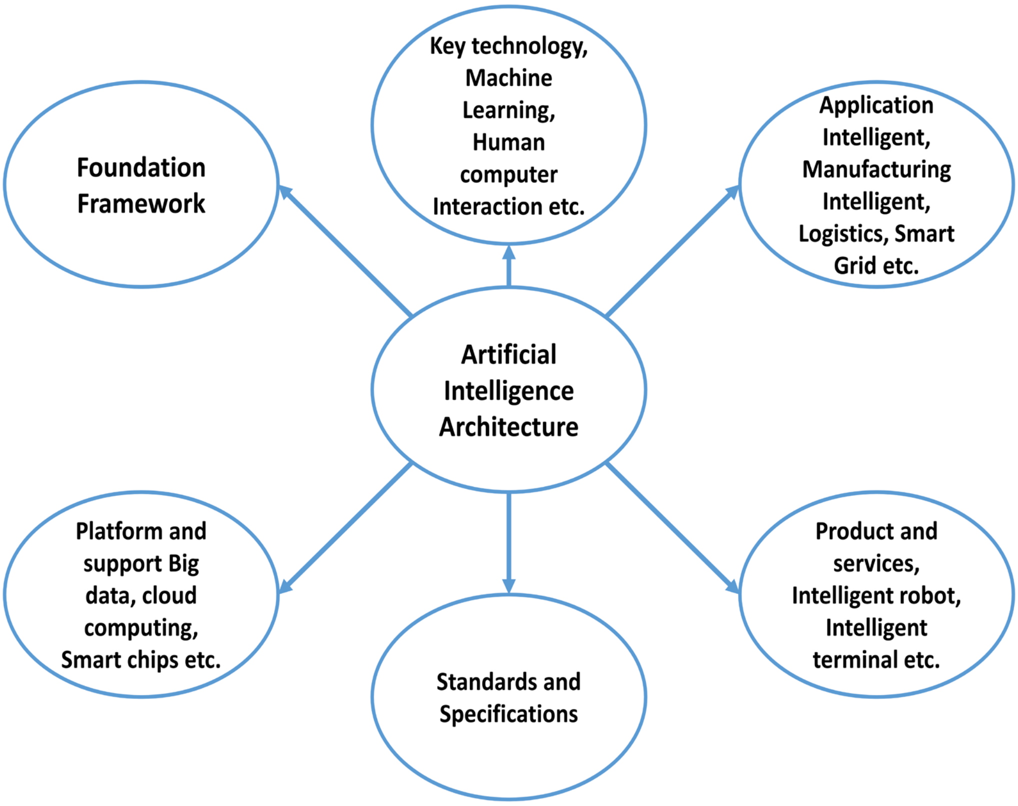



Figure 1-4: AI role in advance areas of technology including SG (Ghofrani et al. 2016)

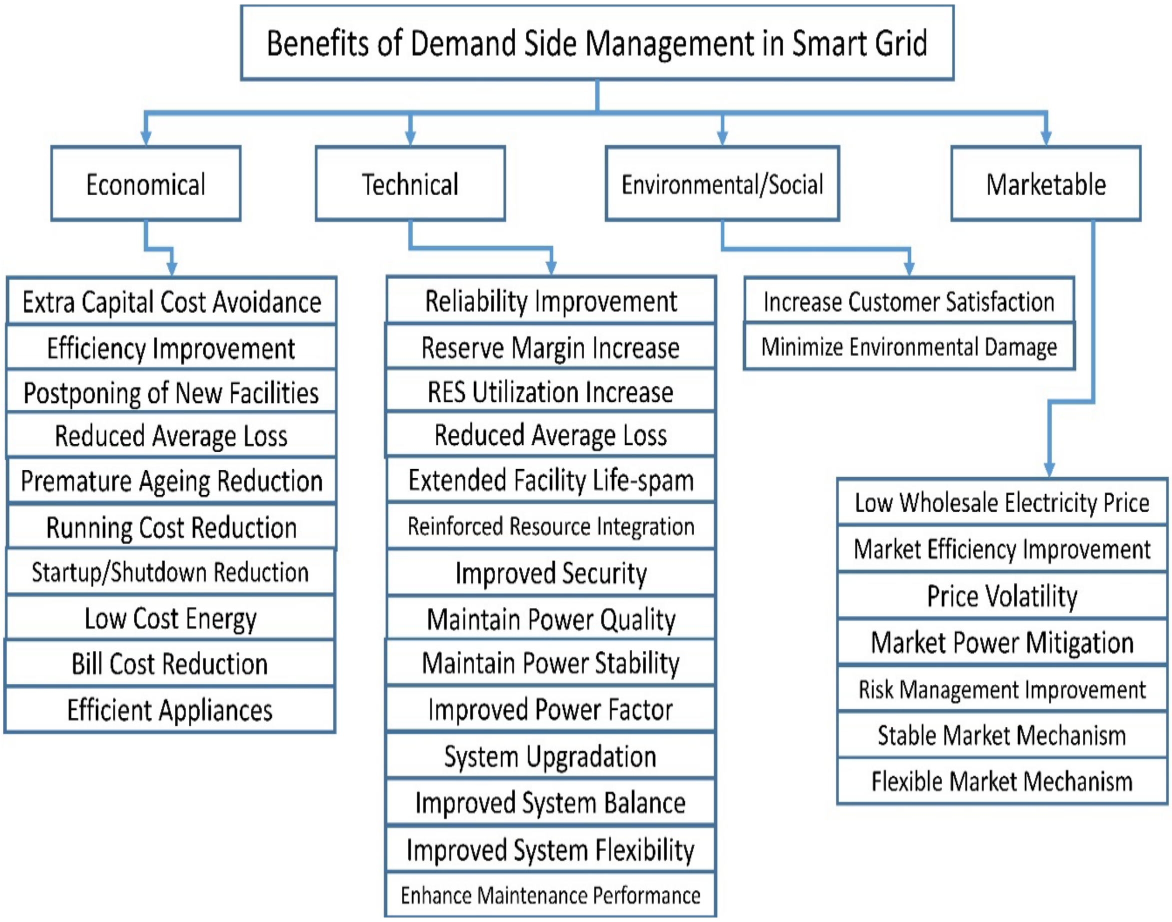



Figure 1-5: Impacts of DSM in SG (Lee et al. 2009)

## 1.1 Aim of the Investigation

The aim of this research is to advance smart grid technology by developing a novel and specialized framework for clustered demand-side energy management (CDEM) using deep neural network (DNN)-based optimization techniques. This framework leverages the predictive and adaptive capabilities of DNNs to enhance energy efficiency, optimize load distribution, and improve grid stability. By integrating clustering techniques with advanced DNN architectures, the research aims to address key challenges in modern energy systems, such as variability in energy demand, renewable energy integration, and peak load management. The findings contribute both theoretical innovations and practical solutions, paving the way for sustainable and efficient energy management in next-generation smart grids.

## 1.2 Objectives of this Research

The achieved objectives for this research are explained below:

1. **Review Literature and Identify Gaps:**

   Examine existing work on energy management and DSM in smart grids to identify key challenges, especially in clustered and predictive optimization methods.

2. **Develop an Integrated Methodology:**

   Create a systematic research approach combining machine learning, particularly DNN, with energy management strategies.

3. **Design a Smart Grid Model with Clustering:**

   Propose a smart grid framework that includes renewable energy, storage, and electric vehicles, using clustering techniques like K-means for user segmentation.

4. **Implement and Optimize DNN for CDEM:**

   Develop a DNN-based model for accurate energy demand forecasting and real-time optimization in clustered demand-side energy management.

5. **Validate and Benchmark the Model:**

   Test the model using simulations and real data, compare it with other techniques, and highlight its practical and theoretical contributions.

## 1.3 Contribution to knowledge

This research contributes to knowledge by developing a novel framework that integrates deep neural networks (DNNs) with advanced optimization techniques for clustered demand-side energy management (CDEM) in smart grids. By leveraging clustering to group users based on energy consumption patterns, the study enables tailored demand response strategies, mitigating peak loads and enhancing grid reliability. The integration of renewable energy sources (RES) and energy storage with DNN-based optimization advances net-zero energy goals, offering scalable and adaptive solutions for modern smart grids. Validated using real-world datasets, the framework outperforms traditional methods in energy prediction, fault detection, and grid stability, providing actionable insights for intelligent and sustainable energy systems.

## 1.4 Problem statement

The increasing demand for energy, combined with the requirement of sustainable energy systems, highlights the critical need for advanced energy management strategies in smart grids. The integration of renewable energy sources, while essential, introduces significant unpredictability, leading to potential imbalances within the grid. Moreover, the variability of energy consumption patterns presents challenges in maintaining a stable and reliable energy supply. Existing methodologies struggle to effectively integrate and utilize diverse data sources, such as historical consumption, real-time sensor data, weather forecasts, and grid parameters into a cohesive optimization framework. This research seeks to address these challenges by developing a novel deep neural network (DNN)-based optimization model for clustered demand-side energy management, offering a sophisticated solution to enhance grid stability, optimize renewable energy usage, and contribute to the advancement of sustainable, resilient energy systems.

## 1.5 Outcome of this Research

The outcomes of this research are the following:

1. Critical analysis of the two-way energy flow in Smart Grid (SG) especially with different Renewable Energy Sources (RES) to meet the customer's dynamic energy requirements.
2. Novel concepts in approaching new techniques and their comparisons for energy management to enhance the use of energy in entire SG.
3. In depth analysis of the Deep Neural Network (DNN) algorithms designed to manage data profiles at different clusters connected from provider to consumer.
4. A novel DNN-based optimisation algorithm tailored for clustered scenarios, demonstrating its effectiveness in real-world smart grid applications.
5. The outcomes of this research are significantly advance the state-of-the-art in smart grid technologies, providing valuable insights and tools for sustainable and adaptive demand-side energy management.

**Neural Networks (NN)**

Neural Networks (NN) is a broad term that refers to computational models inspired by the structure and functioning of biological neural networks. These models consist of interconnected nodes (neurons) organized in layers and are capable of learning from data to perform tasks such as classification, regression, and pattern recognition. The term NN is used generically to describe any neural network architecture, regardless of its complexity or the number of layers it contains. As such, NN is a general term and can apply to both simple and complex neural network structures.

**Artificial Neural Networks (ANN)**

Artificial Neural Networks (ANN) specifically refers to a class of neural networks that simulate the way biological neurons process information. Typically, ANN models are used to describe networks that are not as deep or complex as deep learning models, often consisting of a few layers, usually one hidden layer. The term ANN is used to emphasize simpler networks compared to deeper architectures. While ANN can be used interchangeably with NN in many contexts, it generally refers to a network with fewer layers and less complexity than deep neural networks (DNN).

**Deep Neural Networks (DNN)**

Deep Neural Networks (DNN) are a subset of artificial neural networks characterized by having multiple hidden layers between the input and output layers. The term "deep" refers to the depth of the network, specifically the number of hidden layers that are involved in processing data. DNNs are a key component of deep learning techniques, which have revolutionized areas such as image recognition, natural language processing, and speech recognition. The increased number of layers in DNNs enables them to learn more abstract and hierarchical representations of data, allowing for the modeling of highly complex patterns. While DNNs require larger datasets and more computational resources, they generally outperform simpler neural networks (ANN) on tasks that involve large and complex datasets.

**Why DNN is Preferred for Complex Tasks**

DNNs are considered more powerful than traditional ANNs because their multiple layers allow the network to learn increasingly complex features from data. In tasks such as image classification, the initial layers of a DNN might identify simple features such as edges or textures, while deeper layers can recognize more complex patterns like shapes, objects, or even scenes. This hierarchical learning process enables DNNs to achieve superior performance, particularly in fields that require the recognition of intricate patterns, such as computer vision and natural language processing.

**When to Use Each Term in the Thesis**

**Use "Neural Network (NN)" when:**

1. Referring to neural networks in a broad, theoretical context.
2. Discussing historical developments in machine learning and AI.
3. Explaining fundamental concepts of neural networks, such as activation functions, backpropagation, and weight optimization.

**Use "Artificial Neural Network (ANN)" when:**

1. Referring to classical or shallow architectures (e.g., networks with only one or two hidden layers).
2. Comparing traditional ANNs with advanced architectures (e.g., DNNs, CNNs, RNNs).
3. Discussing earlier energy management models that used basic ANN structures for prediction and classification.

**Use "Deep Neural Network (DNN)" when:**

1. Specifically referring to modern, deep architectures (i.e., networks with three or more hidden layers).
2. Explaining how DNNs outperform shallow ANNs in handling large datasets and complex energy patterns.
3. Discussing applications related to demand-side energy management, clustering, energy load forecasting, optimization, and fraud detection.
4. Referencing case studies and experimental results that involve deep learning techniques.

# Chapter 2: Literature Review

Energy demand has been accelerating significantly in recent years, and this is continuously going to increase in future. According to a recent survey report, by 2050, global industrial energy consumption is projected to exceed 315 quadrillion British thermal units (Btu) (Halder et al. 2015). Coupled with the increasing growth rate of global population the resulting demand rate is also growing. Public safety, economy, and medical services provided to consumers dynamically depends on the stable and consistent availability of power (Esther et al. 2016). The infrastructure of the traditional power grid is static with high response time and inefficient to solve the requests of customers. SG have an advanced energy infrastructure of and communication which is beneficial to change the method of creation, dissemination, and control of power in efficient way (Gungor et al. 2011).

The advancement in IOT enabled devices will facilitate the evolution of traditional electric grids to SG for computational advancement by interconnecting all hubs and apparatuses from provider to consumer side (Halder et al. 2015). The IOT devices are constantly connected with internet at various clusters for DSEM and sharing data from providers to consumers and vice versa. This results the ability to establish and upgrade the services offered to urban communities providing a more stable power supply to consumers. SG integrated with RES is one of example of IOT implementation to get the whole electrical power system more consistent, secure, and effective (Haider et al 2016).

The IOT-based smart apparatuses can be installed and integrated practically in SG infrastructure. Cutting-edge technology refers to the Implementation of advance techniques and approaches implementation in SG will lead to consumers being able to manage their own requirements in real-time dynamically, this will be facilitated by using a smart framework practically. SG is the combined form of efficient smart networks from providers to consumers' end by integrating RES to meet the concept of zero-energy. Advance countries around the globe have begun to adopt a smart network approach in electrical systems, which results the electricity providers are beginning to implement this approach for the benefits of their consumers (Ackermann et al. 2001).

Predetermined correspondence is essential for an efficient SG, which can be achieved by implementing the IOT and ML approaches. Control is present in today's traditional networks, whilst the SG has the ability for perform multiple tasks more efficiently as well as in a secure way. The conventional grid transmission depends on very large electrical cables and transmission lines where in a SG it is also possible to generate power at the distribution side which is more useful to the end-users to fulfil the energy requirements (Lasseter and H 2002).

The consumers of the SG network are dynamically at large numbers and taking part in the framework structure due to needs and requests set while the market of the conventional grid is public and concentrated consumers. The SG designing involves the billions of smart apparatuses, efficient meters, smart sensors, etc. alongside various correspondence advance arrangements whether private or public (Gellings and Clark 2017). Electromagnetic compatibility (EMC) is meaning the devices are compatible due to their electromagnetic environment and it does not emit levels of electromagnetic energy that allows the electromagnetic interface (EMI) with other devices in SG. EMC is an essential process which is require for the design of various devises which are used in SG, which must be considered the continuously real time operation and monitoring where the SG apparatus will operate. However, the security challenges applying Artificial Intelligence (AI) are investigated on the ML and IOT implementation in SG. The AI role in advance areas of technology including the SG is shown in Figure 2-1.

The process protected the versatile DSEM by utilizing the ML approaches to defeat the security issue in the SG. The proposed DSEM is checked by implementing the ML classifier such as DNN to optimise the entire network more efficiently in a secure way and it is possible to control the DSEM of SG at each cluster and consumer's side. A particular Home Area Network (HAN) is assigned to understand the proposed DSEM by implementing DNN (Ding and Zhi 2016). DNN is ultimately human brain modeling with multiple input, hidden and output layers structural configuration. DNN brain working is same as human brain with thousands of parallel processing tasks are working side by side with fully efficient and secure way (Maharjan et al. 2014).

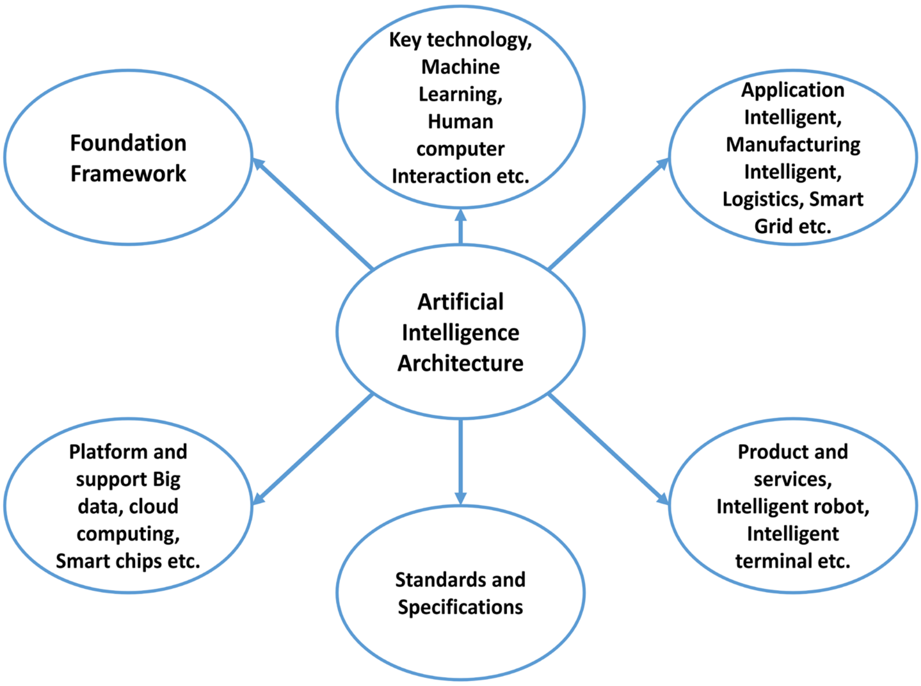



Figure 2-1: AI role in advanced areas of technology including SG (Ghofrani et al. 2016)

The conventional power distribution system is made up of three operational layers like production, transmission, and distribution. In contrast, the modern smart grid (SG) network has introduced numerous enhancements, integrating a large number of renewable energy sources (RES) to meet the energy demands. Furthermore, with the rising costs of oil and coal in this innovative era, there is a global shift toward RES to meet energy needs. To achieve the necessary voltage levels, Boost and Buck converters are employed. The purpose of the SG must be managed to facilitate monitoring, control, interpretation of data and self-healing in addition to ordinary network operations. Therefore, the development of SG is expected to enable networks and its infrastructure that are safe, durable, reliable, and facilitate the integration of RES and SG into public networks (Ding and Zhi 2016). The advancement of energy sources, along with the utilization of specialized household appliances by both consumers and producers, plays a significant role in the development of the smart grid (SG). Important components for managing distributed energy resource management (DSEM) include intricate control systems for monitoring phase angles, voltage levels, frequency, energy management systems (EMS), phasor measurement units (PMU), supervisory control and data acquisition (SCADA), and also for other power and energy constraints. Recent SG research includes automatic generation control (AGC), time management, demand side energy management (DSEM), demand response (DR) advance metering infrastructure (AMI), security for firefighters and installations of information and communication technologies (ICT) (Gungor et al. 2011).

Implementing energy forecasting and demand prediction in real time (the actual time during which a process or event occurs) poses a significant challenge for providers. There is a necessity for effective collaboration between providers and consumers (Ackermann et al. 2001). Predicting energy demand is crucial for meeting energy needs, benefiting customers, providers, and the overall progress of the nation. There are several potential approaches to implement effective control over demand-side energy management (DSEM) as shown in Figure 2-2. SG have a ability to transfer two way communication and power flow efficiently (Lasseter and H 2002). The smart grid (SG) also offers various customers and stakeholders the opportunity to share their energy with the grid, benefiting both customers and providers. A fast communication network is essential for enhancing the overall efficiency and security of the system against potential attacks. While researchers are focusing on improved optimization techniques, the current era of artificial intelligence is pushing for the implementation of machine learning methods (Gellings and Clark 2017). The smart grid (SG) has the capability to monitor all data from providers to consumer appliances; however, generation optimization and voltage monitoring are accomplished through the application of machine learning techniques (Savani 2018). There are several ways to monitor the smart grid intelligence by implementing the ML approaches as shown in Figure 2-3.

AI is implementing in SG to make the system efficient in communication and data processing prospective, however ML have a several techniques and algorithms to optimise the entire system and make it more steadfast and resourceful. DNN is the advance form of ANN to control the DSEM problems as shown in Figure 2-4, and it is one of the most efficient approaches to implement in SG to control the DSEM at various clusters and HAN's. DNN is an intelligent approach for implementation on any direct and indirect modelling with its structural formation of multi-layers. In these inputs, hidden and output layers DNN include large number of datasets to implement on proposed algorithm to obtain the accurate and desired values of output (Dileep 2020).

DNN have the various applications almost in every field in the globe. The uniqueness of using DNN is due to its high efficiency with less response time as compared to any other approach. The output performance is affected if the input layer has limited dataset or any missing values and depends on testing stages from hidden to output layer. DNN modelling only depends on the numerical values and provided data, it makes the DNN modelling less flexible and more efficient (Khare et al. 2018). There are several load balancing techniques which are used in different networks according to situation and demand, which are discussed in Table 2-1, with their pros and cons.

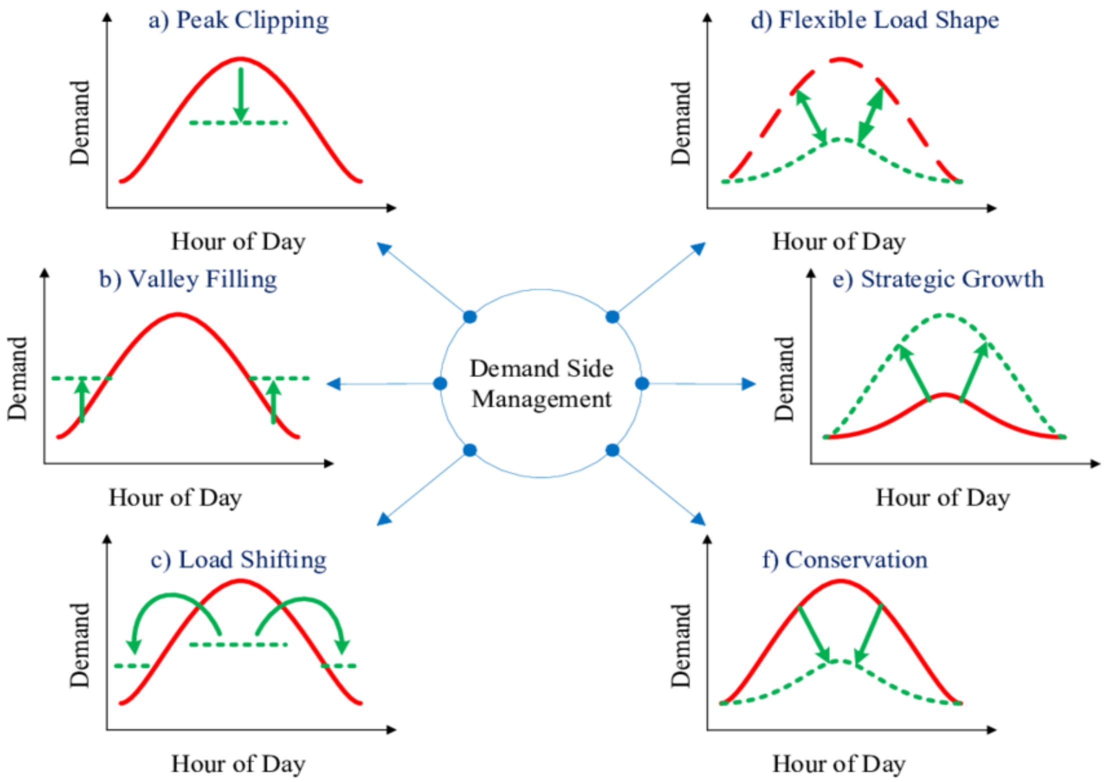



Figure 2-2: Various approaches for DSEM in SG (Song et al. 2014)

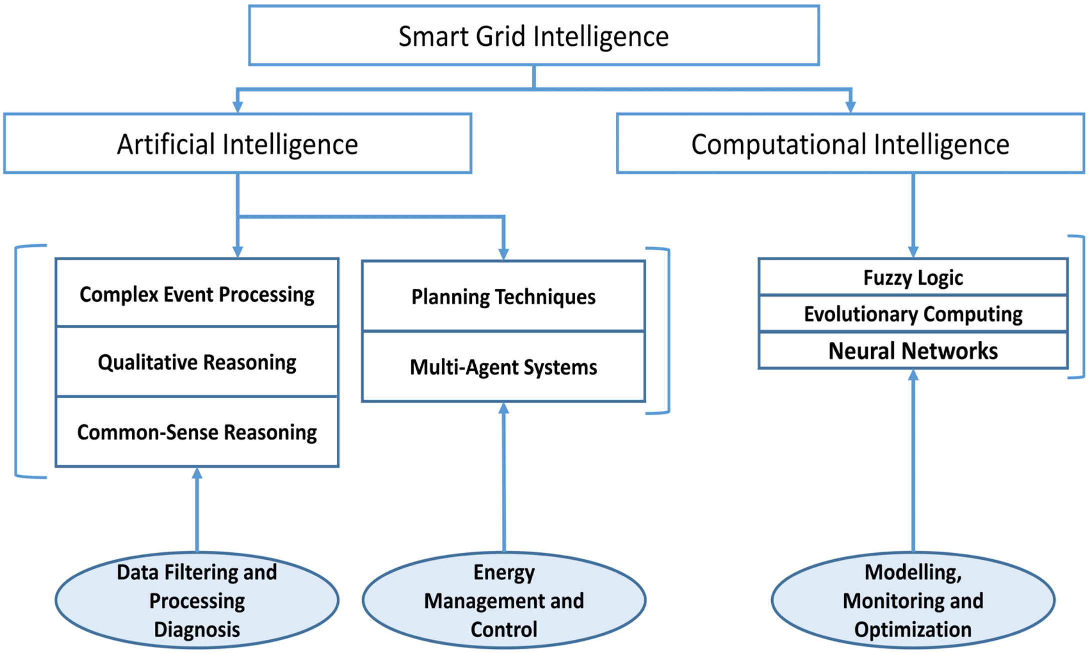



Figure 2-3: ML Implementation for DSEM (Samadi et al. 2012)

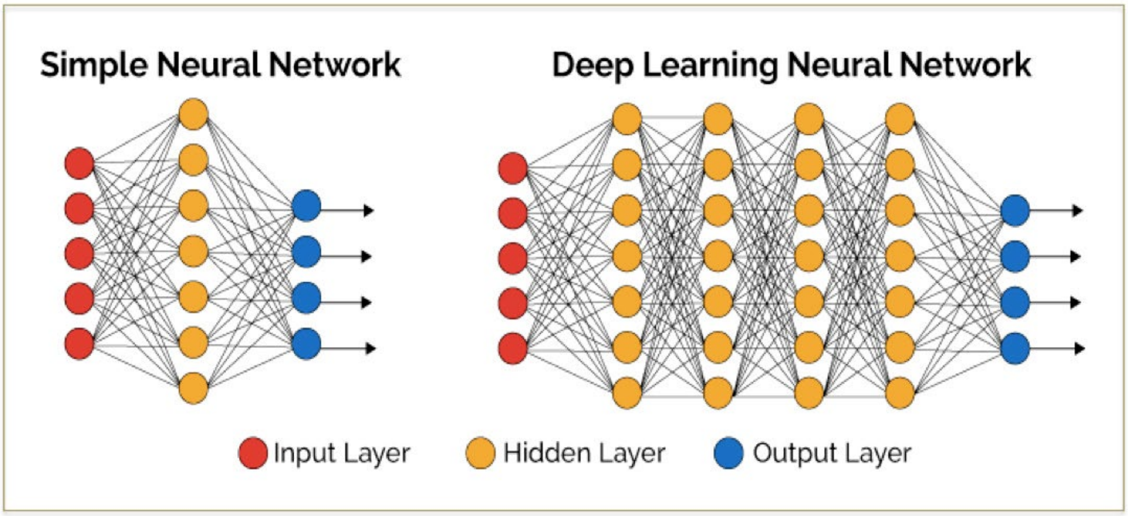



Figure 2-4: DNN Multi-Layers (Bae et al. 2014)

There are several techniques for DSEM, which are further categories according to their types and categories, which are shown in Figure 2-5, and further explanation of each technique is explained in Table  and Table .

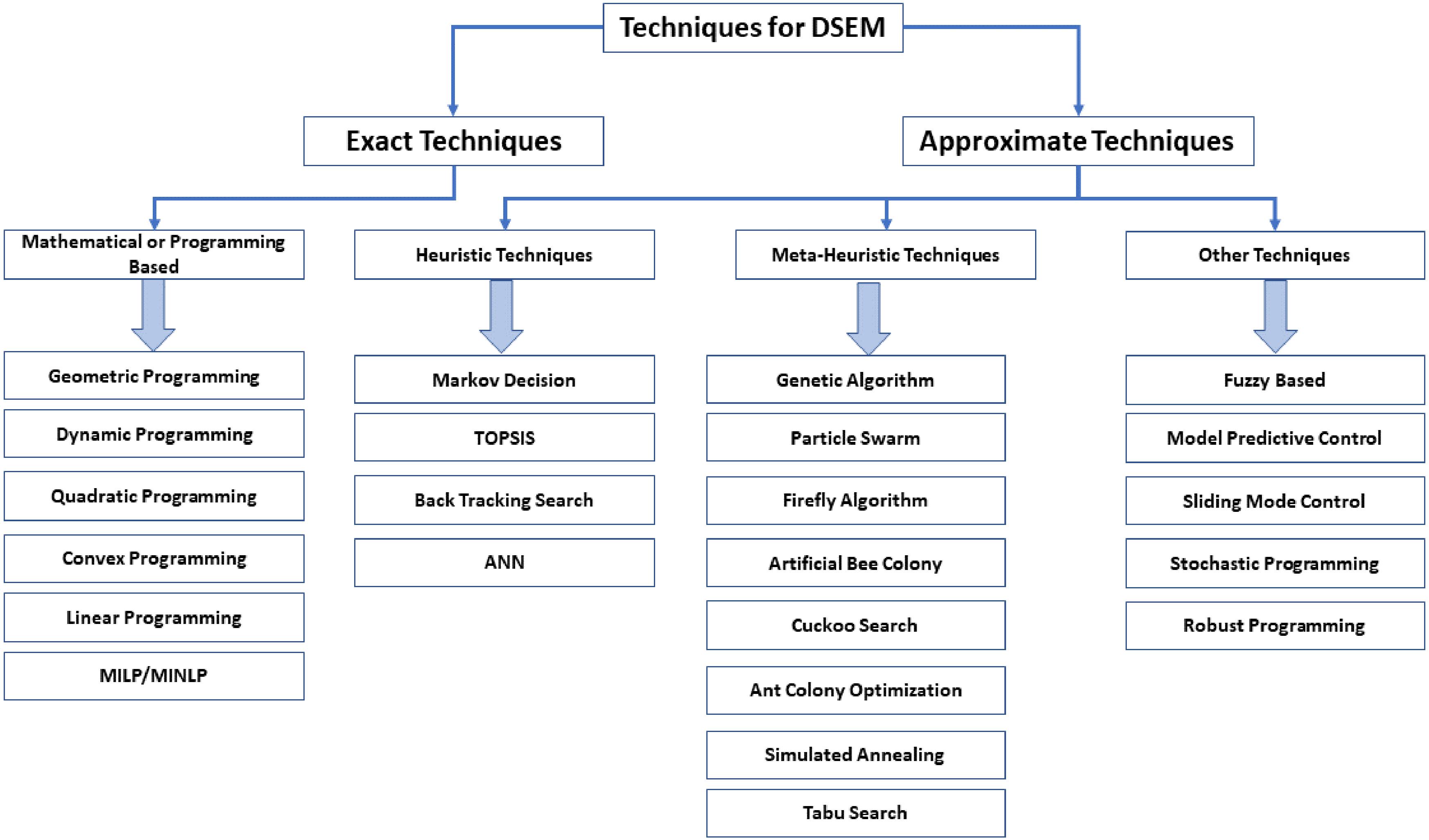



Figure 2-5: Various Techniques for DSEM (Dileep 2020)

## 2.1 Advantages and Disadvantages of various algorithms for DSEM in SG

Table 2-1, illustrates the benefits and drawbacks of numerous algorithms have been presented. Overall, the main benefit of each algorithm is its simplicity and easily implementation, however the drawbacks vary drastically.

Table 2-1: Advantages and Disadvantages of various algorithms for DSEM

| Algorithm | Advantages | Disadvantages | Reference |
|---|---|---|---|
| GA (Genetic Algorithm) | • The GA have a random probability distribution.<br>• It is efficient to perform the multiple tasks in parallel, and deals with multiple dataset values, instead of single point.<br>• It is simple to perform the implementations perspective. The mathematical models and calculations of algorithms solved easily, it's not a complex. | • It is difficult to gain the long term fitness, because it mostly deals with the local optima, instead of global optima, and for the short term fitness.<br>• It is expensive to solve the high dimensional, multimodal, and complex problems. | (Anoune 2018; Koutroulis 2006; Koutroulis 2010; Zeng 2010) |
| PSO (Particle swarm optimisation) | • For scattering the data and for optimisation PSO is easy to implement.<br>• It deals with Simple mathematical calculations.<br>• Sometimes it use the heuristic approach, to find the solution and to achieve the maximum efficiency rates. | • In high dimensional space it falls to local optima easily.<br>• It has a low convergence rate in Iterative process.<br>• Due to conflicting nature, a lot of modifications ate required in algorithms to implement. | (Amer 2013; Ghofrani 2016; Li 2014; Hakimi 2009; Lee 2009; Ardakani 2010; Askarzadeh 2015) |

| | | | |
|---|---|---|---|
| | • It has a fast speed for implementation to deals with multi objective problems. | | |
| ACO (Ant Colony Optimisation) | • It has low time required to solve the complex problems.<br>• It has a good feedback mechanism to deals with simple problems and to optimise the system. | • It is not good to deals with complicated problems due a large number of parameters setting.<br>• In comparison of GA, it's performance is less to deals with complex problems and to achieve the optimise situation. | (Maringer 2005; Adubi 2014; Erdinc 2012) |
| GTA (Game theory algorithm) | • It deals with Simple mathematical calculations, and easy to understand.<br>• It is able to find the best condition and optimisation by implementing the mathematical conditions. | • It is difficult for GTA to solve the complex problems due to high number of mathematical and matrix calculations.<br>• It takes time due to iteration of matrix and calculations. | (Nguyen 2012; Song 2014) |
| LP (Linear Programming) | • It is useful for decision making problems.<br>• It is easy and accurate to deals with linear problems.<br>• It is able to provide and achieve the practical solution. | • It is not useful to implement in Non-Linear problems.<br>• The objective functions and parameters just deals with linear formulation, which is difficult to achieve. | (Nagabhushana 2011; Almunif 2017; Hiremath 2007; Kanase-Patil 2010) |
| Non-LP (Non- Linear Programming) | • To deals with the complex problems the Non-LP is useful to operate. | • It takes a lot of burden to deals with complex problems.<br>• It deals with high number of iterations to solve the numerical problems. | (Siddaiah 2016; Ashok 2007) |

| | | | |
|---|---|---|---|
| DP (Dynamic Programming) | • Easy to implement and to get the state of Global optima and for complex problems.<br>• It is easy to implement in new systems for decision making problems. | • To solve each problems, the DP requires a new parameters and setting of implementations, it is not useful for all problems.<br>• The coding process is difficult and problematic due to large recursive functions. | (Wu, Y., Ravey, A., Chrenko, D, 2019) |

## 2.2 Implementation of different algorithms for DSEM

Table 2-2 describes the detailed analysis and overall summary of optimisation algorithms, the key elements which have been used for the analyzation are the methodology used by each algorithm, percentage decrease in cost of energy and Peak to Average Ratio (PAR).

Table 2-2: Implementation of different algorithms for DSEM

| Algorithm | Methodology | Remarks | Reference |
|---|---|---|---|
| Genetic Algorithm (GA) | Load Shifting Algorithm (Heuristic Based) | The convergence of Algorithm is defined very well and optimised globally. | (Ding et al. 2021) |
| Particle Swarm Optimisation (PSO) Multi-objective, based on the Fuzzy logic techniques. | Demand Response Programs (Probability Model Based) | Factors for the pollution emission and defined very well. | (Aghajani et al. 2017) |
| Game Theory Algorithm (GTA) | Algorithms of Energy Consumptions | The convergence of Algorithm is local. | (Mohsenian-Rad et al. 2010 |
| Particle Swarm Optimisation (PSO) | Algorithm of Load shifting | Less time required for algorithm.<br>The convergence id globally.<br>Have less time of interval. | (Verma et al. 2018) |
| DSEM Algorithm (Non-Stationary) | Algorithm of Incentive compatible | Algorithm is useful for Homogeneous and Heterogeneous Conditions. | (Song et al. 2014) |
| Vickrey Clarke Groov (VCG) | Pricing Methodology (VCG) | Less time required for shifting and execution of algorithm. | (Samadi et al 2012) |

| | | | |
|---|---|---|---|
| | | The convergence of Algorithm is globally. | |
| Distributed algorithm (DA) | Time Varying Pricing | Limited parameters are required to implement the algorithm for residential load optimisation. | (Bae et al. 2014) |
| Game Theory Algorithm (GTA) | DSEM Algorithms (Distributed and Autonomous) | Less execution time is required.<br>The convergence of algorithm is locally. | (Mohsenian-Rad et al. 2010) |
| Linear Programming (LP) | DR Dispatching Model | The algorithm required less time, but unable to deals with large loads and large iterations. | (Wang et al. 2012) |
| Ant Colony Optimisation (ACO) | Management Methodology (Congestion) | It is useful for a hybrid system. | (Liu et al. 2011) |
| Distributed Algorithm (DA) | Energy Scheduling Approach (Autonomous) | Less execution time is required.<br>The convergence of algorithm is locally. | (Mahmood et al. 2014) |
| Gauss-Seidel Algorithm (Sequential Based) | Demand Response Framework (Distributed and Autonomous Optimisation) | Less execution time is required.<br>The convergence of algorithm is locally. | (Yang et al. 2013) |
| Game Theory Algorithm (GTA) | Optimisation Algorithms (Energy storage and consumptions) | The convergence of algorithm is locally and parallel. | (Nguyen et al. 2014) |
| Genetic Algorithm (GA) | Load Shifting (LS) Algorithm | To achieve the value of optimum conditions, algorithm performed well. | (Bharathi et al. 2017) |

## 2.3 Characteristics of Several Algorithms in DSEM

Table 2-3 shows the parameters used by each algorithm with their characteristics, it also elaborates the mechanism used and algorithm type. The main difference in parameter selection of classical methods, metaheuristic and evolutionary algorithm is that the size of population is not of concern in the former algorithm however it is of key interest while selecting the parameters for latter algorithms.

Table 2-3: Different algorithms characteristics for DSEM

| Algorithm type | Algorithm name | Mechanism | User-defined parameters | Characteristics | Reference |
|---|---|---|---|---|---|
| Evolutionary and Heuristic Optimisation Developing Algorithms | Genetic Algorithm (GA) | Natural Selection Mechanism | Probability, Size of Parents and Population | • Chromosomes genes consists of the discrete and continuous values to represent the decision variables.<br>• To create the novel solutions genetic operators are useful and identified.<br>• Pressure and diversity of population effects the method of diversity.<br>• Better termination criteria and optima condition of pressure deals with the correction of convergence. | (Tang 2008; Bozorg-Haddad 2017) |
| | Particle Swarm Optimisation (PSO) | Birds social Behavior | Initial and Final Inertia Weight. The size of the Parents and Population. | • In each dimension the particle position depends on the decision variable.<br>• Position of particle helps to find the optimisation solutions. | Balci 2004; Chuanwen 2005; Jahandideh-Tehrani 2020; |

| | | | | | |
|---|---|---|---|---|---|
| | | | | • The distance between the food and particle represents the fitness functions.<br>• The convergence process relies on termination criteria, the number of iterations, improvements in the objective function, and the runtime of each iteration. | Saadatpour 2013) |
| | Ant Colony Optimisation (ACO) | Ant Species Behavior | Heuristic Information.<br>Parameters for control.<br>Criteria of Termination. | • The path of an ant represents the decision variables.<br>• Distance of ant from nest to food is useful to find the optimisation problems.<br>• Stochastic mechanism is useful to generate the new solutions.<br>• Fitness value of any optimisation solution is useful for decision space of ACO.<br>• Due to the number of iterations, it's useful to find the correction of convergence, and objective functions. | (Afshar 2015; Christodoulou 2010; Merkle 2002) |
| Classical Methods | Linear Programming (LP) | Linear Mathematical Programming | Coefficients Collection.<br>Decision Variables.<br>Constraints.<br>Parameters for Linear Programming. | • LP has a better region of solution.<br>• The optimum solution can be found by the complexity of solutions.<br>• Limited set of constraints is useful to find the objective functions. | (ROBERT 2021; Hillier 2001) |

| | | | | | |
|---|---|---|---|---|---|
| | Non- Linear Programming (Non-LP) | Non-Linear Mathematical Programming | Coefficients Collection.<br>Decision Variables.<br>Constraints.<br>Parameters for Linear Programming. | • Non-LP is useful to deals with complex problems and convert it into a easy solution.<br>• It's useful to find the sequence of sub-division of problems.<br>• It's easy to get the optimum condition of complex problems. | (Mijangos 2005; Qudaih 2011) |
| | Dynamic Programming (DP) | Optimised Multistage Nature | Program involved different parameters to solve each problem. | • To optimise the problems a recursive function is useful.<br>• Method can be categorized to obtain the optimisation situation.<br>• DP is useful to deals with multi-decision functions and process. | (Qudaih and Mitani 2011) |

An extensive literature review on 'Neural Network Implementation for Clustered Demand-Side Energy Management in Smart Grids with Consumers and Prosumers' reveals a dynamic and developing field that intersects smart grid technologies, demand-side management, and artificial intelligence. This review integrates essential findings and insights from the current research, underscoring the present state of knowledge and identifying both trends and gaps in the literature.

In 2022, Philipo, G H, used the technique of neural network for stand-alone solar, PV battery microgrid for energy optimisation, in this research author used the techniques of load shifting and peak clipping (Philipo G. H. Kakande. J. N,  2022). In 2023, a comprehensive review by Elsisi and Amer explored the Internet of Things and different machine learning algorithms, such as reinforcement learning, LSTM, and neural network implementations in electrical systems. The authors determined that neural networks are the most effective solution for handling large datasets in these contexts (Elsisi, Amer, 2023). In 2023, Bakare and Abdulkarim, found the different challenges and their solutions for demand side energy management, authors found that demand response, distributed energy sources and energy efficiency are the three categories of demand side energy management. In 2022, Nand and Ray worked on demand side energy management, with the implementation of genetic algorithm, by using the concept of pump storage device, to balance the energy of provider and consumer, but in this paper there is no solution for two way energy flow, which is the main requirements of prosumers now a days (Nand, Ray, 2022). In 2023, Elsisi and ali, implement the neural network to detect the faults and cyber attacks in electrical system, however, in energy management perspective authors suggests that neural network is the optimise algorithm (Elsisi, ali, 2023).

Neural networks offer valuable insights into energy consumption and production, enabling both consumers and prosumers to make informed decisions regarding their energy usage and generation. However, it is essential to prioritize data privacy and security when implementing smart meter data collection systems. Smart meters are vital to the operation of smart grids. A smart grid represents an advanced electrical network that employs modern communication and control technologies to oversee the flow of electricity from generation to consumption. Smart meters are essential components of smart grids, facilitating two-way pawer flow and communication between consumers and the grid while providing real-time information on energy consumption and production. Smart meters collect data on energy usage at regular intervals, usually every 15 minutes, transmitting this information back to the utility company via a communication network. The utility company can utilize this data to enhance energy distribution, manage peak demand, and respond more swiftly to power outages (F Dewangan, AY Abdelaziz, 2023).

In addition to enabling two-way communication between consumers and the grid, smart meters also allow for more flexible pricing models. With traditional metering systems, consumers pay a fixed rate for their energy usage regardless of when they use it. However, with smart meters, utilities can implement time-of-use pricing models that encourage consumers to shift their energy usage to non-peak times, when energy is cheaper and the grid is under less stress.

Overall, smart meters are a critical component of modern smart grids, providing real-time data and enabling more efficient energy distribution and consumption (N Suhaimy, NAM Radzi, 2022).

There is a direct relationship between the fast demand ramp-up speed and the need for energy storage. Fast demand ramp-up speed refers to the rate at which electricity demand increases in a short period of time. This can happen during peak hours when a large number of consumers are using electricity simultaneously. To meet this sudden increase in demand, the power grid needs to generate more electricity, which can be challenging and expensive.

Energy storage systems can perform a central role in tackling this challenge by supplying electricity during peak demand periods. These systems store surplus electricity produced during times of low demand and release it when demand increases. This approach helps stabilize the grid and decreases the necessity for extra generation capacity. With a faster ramp-up in demand, the need for energy storage to supply electricity rapidly and efficiently increases. Therefore, the importance of energy storage is on the rise, especially as more renewable sources, such as wind and solar, are incorporated into the grid, which is subject to fluctuations in energy output.

Sampling and rapid demand response are crucial concepts in the context of energy storage systems aimed at grid stabilization and balancing. Sampling is the process of measuring and recording data at regular intervals to monitor the performance of an energy storage system. For example, an energy storage system connected to a smart grid could be sampled every few seconds or minutes to measure the amount of energy being stored or discharged. Sampling can help identify any abnormalities or issues with the system and help optimise its performance.

Fast demand response is the ability of an energy storage system to respond quickly to changes in energy demand or supply. This is critical for maintaining grid stability during peak periods or in the event of sudden changes in renewable energy generation. Fast demand response requires energy storage systems to be able to discharge or charge rapidly, typically within seconds or minutes.

When it comes to energy storage systems, the combination of sampling and fast demand response can help optimise their performance and increase grid stability. By monitoring and adjusting the energy storage system's performance through regular sampling, it's possible to ensure that it responds quickly and effectively to changes in demand or supply. This is important for maintaining grid stability, reducing the need for expensive peaking power plants, and maximizing the use of renewable energy resources (MA Judge, A Khan, 2022).

The required minimum and maximum energy storage system for a smart grid will depend on various factors, including the grid's peak demand, renewable energy penetration, and energy usage patterns.

The minimum energy storage system required for a smart grid would be to provide energy storage that can help balance short-term fluctuations in energy supply and demand. This energy storage system should be capable of providing a quick response to any sudden changes in energy demand or supply, such as during peak hours. A minimum energy storage system could be in the form of batteries, flywheels, or capacitors, with a storage capacity of at least 1-2 hours of the grid's peak demand.

The maximum energy storage system required for a smart grid would be to store excess renewable energy generated during off-peak hours and use it during peak hours. This energy storage system should have a larger capacity and be capable of storing energy for longer periods, such as several hours or even days. A maximum energy storage system could be in the form of large-scale battery systems, pumped hydro storage, and compressed air energy storage with a storage capacity of several megawatt-hours.

In summary, the minimum energy storage system for a smart grid would be to provide short-term energy balancing, while the maximum energy storage system would be to store excess renewable energy for use during peak hours. The required energy storage capacity will depend on the specific needs and characteristics of the smart grid system.

A comprehensive literature review on the feasibility of implementing Deep Neural Network (DNN) algorithms within Smart Grid models from the perspectives of consumers and prosumers reveals a growing body of research and practical applications in the field of energy management and distribution. This review provides insights into the key findings and trends in this area:

**Consumer-Centric Research:**

Numerous studies have focused on consumer-centric aspects of Smart Grids and DNNs. These investigations commonly consider the impact on electricity bills, energy efficiency, and user satisfaction. Research by Zhang et al. (2018) demonstrates that DNN-based predictive models can effectively reduce energy consumption for consumers by optimising appliance usage based on historical data. Concerns about data confidentiality and security in Smart Grids are addressed by Li et al. (2019), who propose privacy-preserving DNN algorithms to protect consumers' sensitive information while enabling personalized energy management. Usability and user acceptance are explored by Kim et al. (2020), who emphasize the importance of designing user-friendly interfaces for DNN-based Smart Grid applications.

**Prosumer-Centric Research:**

Prosumers, who actively engage in energy production, have sparked interest in DNN applications for optimising self-consumption and grid integration.

Studies like Wang et al. (2017) investigate DNN algorithms for predicting solar energy generation, enabling prosumers to schedule their energy consumption and exports effectively.

The regulatory environment for prosumers is addressed by Ahlström et al. (2019), who highlight the role of DNNs in ensuring compliance with feed-in tariffs and grid requirements.

Infrastructure requirements and hardware considerations are discussed by Xu et al. (2021), who examine the feasibility of prosumer-scale DNN implementations and their cost-effectiveness.

Intersection of Consumer and Prosumer Perspectives:

Research increasingly explores the convergence of consumer and prosumer roles in Smart Grids. DNNs are seen as tools that can facilitate collaboration and energy sharing within communities. Sun et al. (2020) propose a community-based DNN model that enables energy trading among consumers and prosumers, optimising energy distribution within a microgrid.

**Challenges and Future Directions:**

Common challenges identified in the literature include the need for robust data infrastructure, model interpretability, and addressing potential biases in DNN algorithms.

Future directions in research emphasize the development of DNN algorithms that can adapt to dynamic grid conditions, the integration data sources in real time, and the creation of standardized interfaces for seamless consumer-prosumer participation.

**Practical Implementations:**

Beyond academic research, real-world deployments of DNN-based Smart Grid solutions are gaining momentum. Utility companies and energy providers are leveraging DNNs to enhance grid management, demand response, and predictive maintenance.

Background of research underscores the significance of DNN algorithms in shaping the future of Smart Grids, with a particular focus on consumers and prosumers. As researchers and practitioners continue to explore the feasibility, benefits, and challenges of DNN-based applications in this context, the body of knowledge surrounding this subject is poised to expand, contributing to more efficient, reliable, and consumer-oriented energy systems.

Over the last five years (2020–2025), Demand-Side Energy Management (DSEM) has emerged as a pivotal area of research within the smart grid domain, particularly in response to the growing integration of consumers and prosumers. A wide spectrum of methodologies has been investigated to optimise energy consumption patterns, enhance grid reliability, and support the transition towards sustainable energy systems. This literature review presents a comprehensive examination of these approaches, critically analysing their roles, practical implementations, and contributions to the advancement of DSEM frameworks.

**Rule-Based Techniques** have been foundational in DSEM, employing predefined policies and pricing schemes to influence consumer behaviour. Time-of-Use (ToU) pricing, for instance, encourages consumers to shift their energy usage to off-peak periods by offering lower rates during those times. Zou, Bin, et al. (2022) discussed the implementation of ToU pricing to manage electricity demand across various sectors, highlighting its effectiveness in load shifting and peak demand reduction. Similarly, Real-Time Pricing (RTP) reflects the real-time cost of electricity, providing price signals that incentivize consumers to adjust their consumption accordingly.

Trinh, H. A., Truong, H. V. A (2022) also explored RTP as a means to enhance demand response strategies, emphasizing its role in promoting energy efficiency. Critical Peak Pricing (CPP) imposes higher prices during critical peak periods to discourage excessive energy use, a method analysed by Williams et al. (2023) for its potential in managing peak demand effectively. Inclining Block Rates (IBR), which charge higher rates as consumption increases to promote energy conservation, were examined by Williams et al. (2023) in the context of residential energy management. While these methods are straightforward and easy to implement, their effectiveness can be limited by consumer awareness and responsiveness. Recent studies have explored integrating these pricing schemes with advanced technologies to enhance their impact.

In the realm of **Classical Optimization Techniques**, methods such as Linear Programming (LP), Mixed-Integer Linear Programming (MILP), Non-Linear Programming (NLP), and Dynamic Programming (DP) have been extensively applied to DSEM problems to achieve optimal energy distribution and cost minimization. Xie, P., Guerrero, J. M. (2021) worked on the comprehensive review highlighted the application of LP in energy management systems, noting its utility in optimizing energy scheduling in microgrids. MILP has been employed to address problems involving both continuous and discrete variables, making it suitable for unit commitment and load scheduling. The same review discussed the use of MILP in optimizing energy management strategies, emphasizing its versatility in handling complex decision variables. NLP has been utilized to handle complex systems with non-linear constraints, often in optimizing renewable energy integration. The review explored the application of NLP in energy management systems, highlighting its effectiveness in modelling the non-linear characteristics of energy systems. DP, applied in scenarios requiring multi-stage decision-making such as battery storage management, was also highlighted for its role in developing optimal control policies over time. These techniques provide precise solutions but may suffer from scalability issues when applied to large-scale systems.

To overcome the limitations of classical methods, **Heuristic and Metaheuristic Techniques** have been employed for their ability to find near-optimal solutions within reasonable computational times. Genetic Algorithms (GA), inspired by natural selection, have been used to optimize load scheduling and energy storage management (Zheng, Z., Yang, S (2023)). A comprehensive review discussed the application of GA

in demand-side management strategies, noting its effectiveness in exploring large solution spaces. Particle Swarm Optimization (PSO), modelling the social behaviour of particles, has been applied in demand response programs to find optimal solutions. The same review explored the use of PSO in optimizing energy management strategies, highlighting its convergence properties. Ant Colony Optimization (ACO), simulating the foraging behaviour of ants, has been utilized to solve complex optimization problems in energy management. The review highlighted the application of ACO in demand-side management strategies, emphasizing its ability to find good solutions in combinatorial problems. Artificial Bee Colony (ABC), based on the foraging behaviour of honeybees, has been applied in optimizing energy consumption patterns. (Liemthong, R., Srithapon, C. (2022)) discussed the use of ABC in energy management systems, noting its simplicity and effectiveness. Differential Evolution (DE) has been utilized for optimizing continuous spaces in energy scheduling tasks. The review explored the application of DE in demand-side management strategies, highlighting its robustness. Simulated Annealing (SA), emulating the annealing process in metallurgy, has been used to find optimal or near-optimal solutions in energy management. The review highlighted the use of SA in optimizing energy management strategies, noting its ability to escape local optima. These algorithms are particularly useful in handling the non-linear and complex nature of DSEM problems.
**Game-Theoretic Approaches** have been applied to model the strategic interactions between various stakeholders in the energy market. Non-cooperative games consider scenarios where each participant aims to maximize their own benefit without collaboration. A comprehensive review by Liu, X., Ji, Z., Sun (2022) discussed the application of non-cooperative game theory in demand-side management strategies, highlighting its relevance in competitive energy markets. Cooperative games focus on coalition formation among participants to achieve collective benefits. The same review explored the use of cooperative game theory in optimizing energy management strategies, emphasizing the advantages of collaborative approaches. Stackelberg games involve leader-follower dynamics, often used to model interactions between utilities and consumers. The review highlighted the application of Stackelberg game theory in demand-side management strategies, noting its applicability in hierarchical decision-making scenarios. Evolutionary game theory studies the evolution of strategies over time within a population of agents. The review discussed the use of evolutionary game theory in understanding the adaptation of consumer behaviours in

energy markets. These approaches provide insights into designing incentive mechanisms and understanding market dynamics in DSEM.

**Control-Based Techniques** are essential for real-time energy management and system stability. Model Predictive Control (MPC) utilizes a model of the system to predict and optimize future behavior, applied in energy storage control. A study by Tumeran, N. L., Yusoff, S. H (2023) systematically reviewed predictive control applications in energy systems, particularly in electric vehicle integration and bidirectional energy exchange, highlighting the effectiveness of MPC in handling constraints and multi-objective optimization. Fuzzy Logic Control (FLC) handles uncertainties and imprecise information, suitable for consumer load control. A study designed an FLC that considers intermittent renewable sources

The rapid transformation of electrical power systems into smart grids has necessitated the adoption of advanced technologies for efficient energy management (Kumar, G., Kumar, L (2023)). Traditional demand-side energy management strategies have struggled with the increasing complexity of energy systems, driven by high penetration of distributed energy resources (DERs) and dynamic consumer behaviour. In response, deep neural networks (DNNs) have emerged as a powerful tool for optimizing energy consumption, improving demand response, and enhancing grid stability.

Smart grids are evolving with the incorporation of artificial intelligence (AI) and machine learning techniques, particularly DNNs, which have shown remarkable performance in predicting energy demand, managing loads, and optimizing renewable energy integration (Ali, A. O., Elmarghany, M. R., Abdelsalam (2022)). Recent research has emphasized the importance of data-driven approaches for energy management, leveraging smart meters, Internet of Things (IoT) devices, and advanced metering infrastructure (AMI) to gather and process real-time energy consumption data.

This research provides a comprehensive literature review on deep neural network-based optimization techniques for clustered demand-side energy management (CDEM) in smart grids. Recent advancements in AI, data-driven clustering methods, and machine learning-based energy forecasting are discussed, along with their impact on achieving net-zero energy goals.

**Comparison of DNN with Other Techniques**

| Technique | Example Algorithms | Pros | Cons |
|---|---|---|---|
| Rule-Based Techniques | ToU, RTP, CPP | Simple to implement, low computational cost | Rigid, lacks adaptability, limited scalability |
| Classical Optimization | LP, MILP, NLP, DP | Optimal and accurate for well-defined problems | Not scalable for large problems, sensitive to constraints |
| Heuristic/Metaheuristic | GA, PSO, ACO, DE | Good for complex and nonlinear problems, flexible | May converge to local optima, tuning is complex |
| Game-Theoretic Approaches | Stackelberg, Cooperative Game | Models strategic behavior among agents, suitable for market dynamics | Requires precise utility modeling, complex implementation |
| Control-Based Techniques | MPC, FLC, MAS | Real-time control, handles dynamic systems | Needs accurate system modeling, limited learning ability |
| Machine Learning | SVM, Decision Trees, Reinforcement Learning | Good prediction accuracy, less data-intensive than deep learning | May struggle with unstructured data, requires feature engineering |
| Deep Learning (DNN) | DNN, CNN, LSTM, DRL | Highly accurate, can learn complex nonlinear patterns, handles large data | Needs large datasets and high computing power, black-box nature |

## 2.4 Summary of Literature Review

The SG employs the demand side energy management (DSEM) for electrical energy savings, which refers to adaption of customer's demand of energy by implementing the various techniques and algorithms. Overall, globally different researchers are doing work for energy management from providers to consumers end at electrical networks to enhance the efficiency of energy by overcome the demand side energy problems. However, each technique as mentioned in literature review (Table-1-Table-3) have its own benefits and drawbacks. The Figure 2-6 explains the overall challenges facing in DSEM, by implementing the different traditional to evolutionary algorithms.

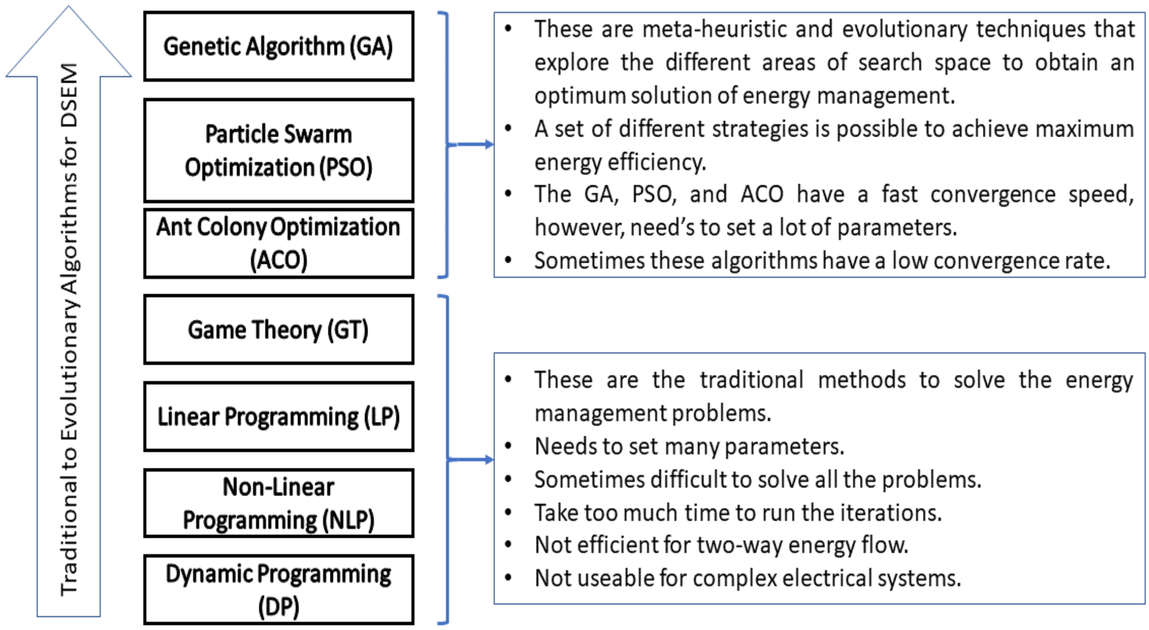



Figure 2-6: Overall comparison of algorithms for DSEM

The proposed research is to implement optimal control and efficient operation of Smart Grid Distribution Network (SGDS) by implementing the Deep Neural Network (DNN) algorithm to improve the energy management and optimum power flow.

The DNN can control the information management from the acquired data of customer's and clusters of various consumers, according to the requirement of customers and grid operators. The optimised implementation of DNN can process these clusters to monitor and control the power flow between:

- Provider – Consumer (PR-C)
- Prosumer – Consumer (PRS-C)
- Prosumer – Provider – Consumer (PRS-PR-C)

By considering the number of parameters and computation, Deep Neural Networks (DNN) are the most efficient networks as compared to any other type because at every layer, deep neural network is able to get a clearer and abstract depiction of the input data.

Dataset depends on the number of providers, prosumers and consumers attached with the electrical system. If the dataset has large number of data, then the training of DNN will be more accurate and perfect. Traditional ML techniques are preferable when dealing with small quantities of data. When it comes to complicated issues, deep learning really shines.

# Chapter 3: Designing, Implementation and significance of Deep Neural Network in Electrical Power Systems

This chapter presents a detailed exploration of the design and implementation of Deep Neural Networks (DNNs) for optimising demand-side energy management (DSEM) within smart grid systems. The chapter begins by outlining the fundamental architecture of DNNs and their significance in accurately forecasting energy demand in increasingly decentralised and dynamic power systems. Load prediction plays a critical role in balancing supply and demand, particularly in smart grids that integrate large-scale renewable energy sources such as solar and wind. DNNs are well-suited for this task due to their ability to model complex, non-linear relationships and to learn temporal patterns in consumption and generation data.

The chapter also provides a systematic overview of the implementation steps required to integrate DNNs into electrical systems. These include data preprocessing, training, testing, and validation procedures using real-time and synthetic datasets. Emphasis is placed on how DNNs support real-time energy scheduling by forecasting load and generation, thereby enabling improved control over grid variables such as voltage and frequency. The capability of DNNs to perform under varying operational conditions enhances grid responsiveness and supports proactive energy management.

A significant contribution of this chapter is the comparative evaluation of DNNs with other widely used techniques, including Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). Simulation results show that the DNN model consistently outperforms PSO and GA in terms of prediction accuracy, mean absolute error (MAE), root mean square error (RMSE), and $R^2$ score. These findings empirically validate the superiority of deep learning approaches over traditional heuristic optimisation methods for energy forecasting and scheduling.

Furthermore, the chapter investigates the impact of clustering on DNN performance. By applying K-means clustering to group consumers and prosumers based on similar energy consumption and generation patterns, multiple DNN models are trained on homogeneous subsets of data. The comparative results between clustered and non-clustered DNN implementations demonstrate that clustering significantly improves prediction accuracy, reduces model error, and enhances convergence efficiency. This clustering-based DNN framework proves to be a highly effective strategy for managing energy in large-scale systems involving diverse users.

## 3.1 Deep Neural Networks

Deep Neural Networks (DNNs) draw inspiration from the functioning of the human brain, which processes vast amounts of information through data received from the senses. In terms of parameters and computational efficiency, DNNs stand out as the most effective networks compared to others, as they can produce increasingly clear and abstract representations of input data at each layer. The primary advantages of Deep Neural Networks is the ability to automatically extract features and adjust them to achieve desired outcomes. This neural network-based approach is applicable to a variety of applications and diverse datasets. Furthermore, the flexible architecture of deep learning allows it to adapt to new challenges that may arise in the future.

## 3.2 Practical Applications of proposed technique

Demand side energy management (DSEM) is an valuable function of Smart Grid (SG) and it helps to deduce the utilization costs of electricity. It allows energy providers, consumers and prosumers to reduce the peak demand of energy. DSEM in RES integrated SG refers to those steps and technologies which encourage the consumers and prosumers to optimise their energy use. The benefits of DSEM for consumers and prosumers is to reduction in electricity bills by adjusting the timing and amount of energy use.

DSEM implementation consists of monitoring and planning of electric utilities from providers to consumers and prosumers side to modify their level and pattern of energy usage. Different electrical companies use DSEM to forecast and plan of how to meet energy demand for services and products. The proposed algorithm of DNN implementation in RES integrated SG identifies and enables the providers to consumers and prosumers side to schedule their loads to minimise the cost, fulfil the energy demand to optimise the entire electrical network of SG.

### 3.2.1 Progress in relation to methodology

Neural Networks have much importance for prediction, pattern recognition, classification and optimisation of electrical networks. Especially, Neural Networks have the capacity to measure and organize the large amount of energy data, which is very useful in S.G and in those systems where RES are connected and there is a two-way energy flow.

Neural Networks is the most optimised technique for energy management, when "N" number of consumers and prosumers (with different energy sources, like solar, wind and batteries) are integrated with the electrical system, as shown in Figure 3-1.

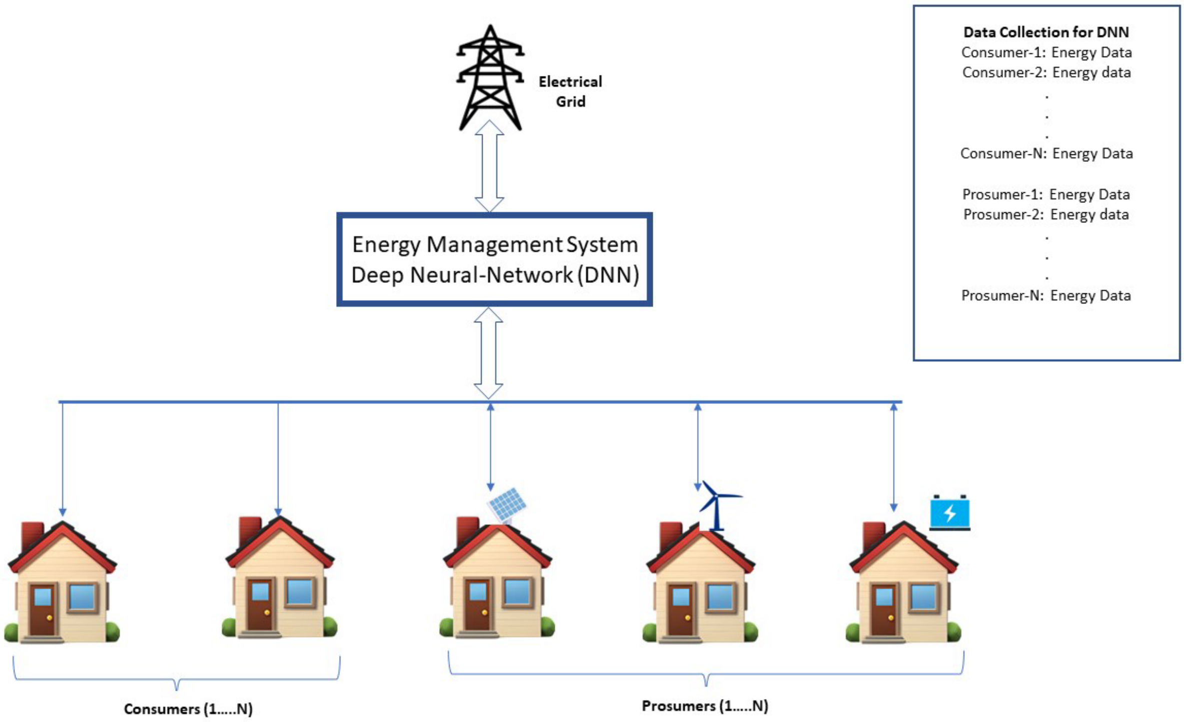



Figure 3-1: Integration of Consumers and Prosumers in the Electrical System

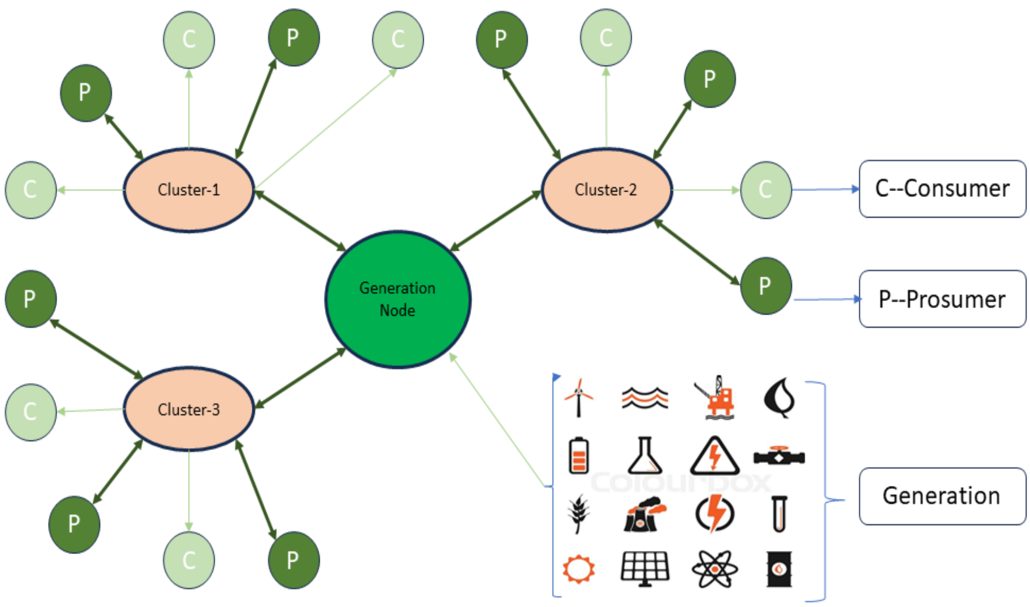



Figure 3-2: Clustering Phenomenon of Consumers and Prosumers with Generation Node

In Figure 3-2, there is a clustering phenomenon of consumers and prosumers in which there are three clusters integrated with the generation node and also with the consumers and prosumers at demand side.

**Collection of Data:**

The given data of smart grid is taken from the repository of California university, and can be found by using the following link,

(https://archive.ics.uci.edu/dataset/471/electrical+grid+stability+simulated+data).

The researchers (B. Schafer, C Grabow, 2016) implemented the above-mentioned data for taming (make less powerful and easier to control) variabilities in electrical networks by using the decentralized control. In this research, there is the concept of linear stability and basin volume of attraction for a dynamically system, when renewable sources are integrated with the system. The researchers used the frequency deviation check technique to check the stability of the system in perspective of power, price and time. The original dataset of above-mentioned research is shown in Table 3-1. To calculate the basin of attraction for a specific electrical system is a complex task that typically requires numerical simulations and computational techniques. The volume of the basin of attraction depends on the specific equations governing the dynamical system and the properties of the electrical system (Field Y, Hartmann A.K. 2019).

For the calculation of stability of the system, there are several steps involves for the basin of attraction to find the exact points of a dynamically system and it's stability (Y Du, Q Li, 2022). These steps are the following:

- Define the exact dynamically system.
- Identify the attractor (Such as fixed point, limit cycle and strange attractor)
- Numerical simulations
- Volume estimation of the system

In this research (B. Schafer, C Grabow, 2016) the authors determine the fourteen columns data, in which "tau" represents the reaction time, "p" represents the nominal power and "g" denotes to the price elasticity of customers in a dynamical system. In this Table 3-2, of data, tau1, p1, and g1 are for the generation node, and remaining three values are for the consumption node. From the frequency deviation check, authors find the stability of the system, in which there is a calculation of angular frequency check by examine the rotor angle for each dynamically machine as shown in below equation.

$$\frac{\mathrm{d}^2\theta_i}{\mathrm{d}t^2} = P_i - \alpha_i \frac{\mathrm{d}\theta_i}{\mathrm{d}t} + \sum_{j=1}^{N} K_{ij} \sin(\theta_j - \theta_i) \quad \forall i \in \{1, \ldots, N\}$$

Where θ is the rotor angle, α is the damping factor, P is the power, and K is the accoupling strength of each point. If the calculated value of the stability is positive then the system is unstable, otherwise for negative, it's stable.

Table 3-1: The original dataset (20 values out of 60k) of mentioned research (***B. Schafer, C Grabow***, 2016)

| 1 | tau1 | tau2 | tau3 | tau4 | p1 | p2 | p3 | p4 | g1 | g2 | g3 | g4 | stab | stabf |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 2.95906 | 3.079885 | 8.381025 | 9.780754 | 3.763085 | -0.7826 | -1.25739 | -1.72309 | 0.650456 | 0.859578 | 0.887445 | 0.958034 | 0.055347 | unstable |
| 3 | 9.304097 | 4.902524 | 3.047541 | 1.369357 | 5.067812 | -1.94006 | -1.87274 | -1.25501 | 0.413441 | 0.862414 | 0.562139 | 0.78176 | -0.00596 | stable |
| 4 | 8.971707 | 8.848428 | 3.046479 | 1.214518 | 3.405158 | -1.20746 | -1.27721 | -0.92049 | 0.163041 | 0.766689 | 0.839444 | 0.109853 | 0.003471 | unstable |
| 5 | 0.716415 | 7.6696 | 4.486641 | 2.340563 | 3.963791 | -1.02747 | -1.93894 | -0.99737 | 0.446209 | 0.976744 | 0.929381 | 0.362718 | 0.028871 | unstable |
| 6 | 3.134112 | 7.608772 | 4.943759 | 9.857573 | 3.525811 | -1.12553 | -1.84597 | -0.55431 | 0.79711 | 0.45545 | 0.656947 | 0.820923 | 0.04986 | unstable |
| 7 | 6.999209 | 9.109247 | 3.784066 | 4.267788 | 4.429669 | -1.85714 | -0.6704 | -1.90213 | 0.261793 | 0.07793 | 0.542884 | 0.469931 | -0.01738 | stable |
| 8 | 6.710166 | 3.765204 | 6.929314 | 8.818562 | 2.397419 | -0.61459 | -1.20883 | -0.574 | 0.17789 | 0.397977 | 0.402046 | 0.37663 | 0.005954 | unstable |
| 9 | 6.953512 | 1.379125 | 5.7194 | 7.870307 | 3.224495 | -0.749 | -1.18652 | -1.28898 | 0.371385 | 0.633204 | 0.732741 | 0.380544 | 0.016634 | unstable |
| 10 | 4.689852 | 4.007747 | 1.478573 | 3.733787 | 4.0413 | -1.41034 | -1.2382 | -1.39275 | 0.269708 | 0.250364 | 0.164941 | 0.482439 | -0.03868 | stable |
| 11 | 9.841496 | 1.413822 | 9.769856 | 7.641616 | 4.727595 | -1.99136 | -0.85764 | -1.87859 | 0.376356 | 0.544415 | 0.792039 | 0.116263 | 0.012383 | unstable |
| 12 | 5.93011 | 6.730873 | 6.245138 | 0.533288 | 2.327092 | -0.7025 | -1.11692 | -0.50767 | 0.239816 | 0.56311 | 0.164461 | 0.753701 | -0.02841 | stable |
| 13 | 5.381299 | 8.014521 | 8.095174 | 6.769248 | 5.507551 | -1.97271 | -1.84933 | -1.6855 | 0.359974 | 0.173569 | 0.349144 | 0.62886 | 0.02813 | unstable |
| 14 | 1.616787 | 2.939228 | 0.819791 | 4.191804 | 3.752282 | -1.48488 | -1.28058 | -0.98682 | 0.899698 | 0.866546 | 0.303921 | 0.07761 | -0.04862 | stable |
| 15 | 8.551598 | 8.314952 | 2.549964 | 9.926807 | 4.891714 | -1.80863 | -1.16706 | -1.91603 | 0.612404 | 0.280983 | 0.354342 | 0.472192 | 0.027756 | unstable |
| 16 | 1.132108 | 2.920324 | 8.951079 | 7.248583 | 5.033681 | -1.84608 | -1.36278 | -1.82482 | 0.352292 | 0.524173 | 0.599004 | 0.67439 | 0.01488 | unstable |
| 17 | 7.021362 | 4.374294 | 4.775904 | 8.838426 | 3.335857 | -0.96239 | -1.40763 | -0.96584 | 0.7111 | 0.625364 | 0.468335 | 0.895143 | 0.072508 | unstable |
| 18 | 4.952241 | 8.088672 | 8.883319 | 5.694557 | 5.067296 | -1.68141 | -1.87706 | -1.50882 | 0.305662 | 0.307904 | 0.889894 | 0.879428 | 0.065617 | unstable |
| 19 | 4.14283 | 2.439089 | 1.290456 | 9.456443 | 3.934796 | -1.4693 | -1.76694 | -0.69856 | 0.800757 | 0.840807 | 0.917833 | 0.793982 | -0.00697 | stable |
| 20 | 9.346126 | 7.92003 | 2.335276 | 3.269181 | 4.581174 | -1.10675 | -1.74708 | -1.72734 | 0.836076 | 0.713254 | 0.161518 | 0.515983 | 0.041374 | unstable |

**Implementation:**

According to the proposed research, there is a need of power/energy data for a dynamical electrical system, when renewable sources are integrated with the system to meet the concept of smart grid and zero energy building. It's the reason, in this research, the data is used for energy perspectives, by implementing the concept of clustering technique with deep neural networks for demand side energy management. The all values of the mentioned dataset is taken from the smart meter with the duration of 0.5s-10s. In Table 3-1, the tau1, p1, and g1 are the values of reaction time, nominal power and price respectively of generation node, and tau2, tau3, and tau4 is the reaction time of consumption nodes, and similarly p2, p3, and p4 are the nominal power and g2, g3 and g4 are the price values of three consumption nodes.

Table 3-2: Proposed Energy data containing the 60k values

| 1 | P | C-1 | C-2 | C-3 | stab | stabf |
|---|---|---|---|---|---|---|
| 2 | 3.763085 | -0.7826 | -1.25739 | -1.72309 | 0.055347 | unstable |
| 3 | 5.067812 | -1.94006 | -1.87274 | -1.25501 | -0.00596 | stable |
| 4 | 3.405158 | -1.20746 | -1.27721 | -0.92049 | 0.003471 | unstable |
| 5 | 3.963791 | -1.02747 | -1.93894 | -0.99737 | 0.028871 | unstable |
| 6 | 3.525811 | -1.12553 | -1.84597 | -0.55431 | 0.04986 | unstable |
| 7 | 4.429669 | -1.85714 | -0.6704 | -1.90213 | -0.01738 | stable |
| 8 | 2.397419 | -0.61459 | -1.20883 | -0.574 | 0.005954 | unstable |
| 9 | 3.224495 | -0.749 | -1.18652 | -1.28898 | 0.016634 | unstable |
| 10 | 4.0413 | -1.41034 | -1.2382 | -1.39275 | -0.03868 | stable |
| 59991 | 3.406522 | -1.77496 | -0.57999 | -1.05157 | 0.008634 | unstable |
| 59992 | 4.587533 | -1.59414 | -1.95057 | -1.04282 | 0.028673 | unstable |
| 59993 | 3.660232 | -1.10564 | -1.10352 | -1.45107 | 0.00826 | unstable |
| 59994 | 2.673156 | -0.65274 | -0.91819 | -1.10223 | 0.064645 | unstable |
| 59995 | 5.19925 | -1.71321 | -1.71703 | -1.76901 | 0.050212 | unstable |
| 59996 | 3.783797 | -0.66247 | -1.63991 | -1.48142 | 0.026311 | unstable |
| 59997 | 3.343416 | -1.44911 | -0.65805 | -1.23626 | 0.023892 | unstable |
| 59998 | 4.349512 | -0.95244 | -1.66366 | -1.73341 | -0.0258 | stable |
| 59999 | 4.299976 | -0.94388 | -1.38072 | -1.97537 | -0.03181 | stable |
| 60000 | 2.514755 | -0.64991 | -0.96633 | -0.89851 | 0.037789 | unstable |
| 60001 | 3.492807 | -1.53219 | -1.39029 | -0.57033 | 0.045263 | unstable |

The proposed data as shown in Table 3-2 is used for energy management perspectives, in which renewable sources are integrated with the system. Clustering technique through deep neural network is used to check the stability of the system to optimise the overall network from generation to demand side.

The proposed data of power p1, p2, p3, and p4 are replaced with generation node (P), and cluster-1 (C-1), cluster-2 (C-2), and cluster-3 (C-3) respectively, to implementing the clustering technique with deep neural network for demand side management, when each cluster is connected with the generation node and also with different types of consumers and prosumers for energy management. However, if the stability (stab) value is positive, the overall system is unstable, and each stab value is determined in the above-mentioned research by the frequency deviation check in the system.

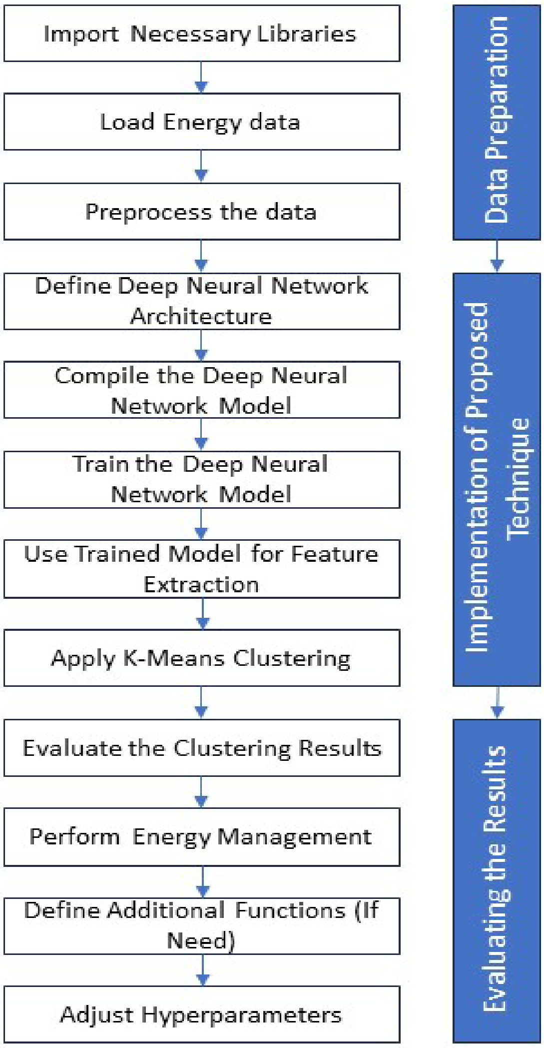



Figure 3-3: Proposed Algorithm Steps for Implementation

In Figure 3-3, there are steps mentioned for the proposed algorithm, which is implemented by using the python programming, Anaconda-Jupyter Notebook/Colabresearch, however, the designing of deep neural network models is explained with each step in section 3.3.

### 3.2.2 Results and Discussion

For the implementation of proposed technique for clustering and neural network algorithm, there is "Displot" and "Hisplot", commands are used in the code. After implementing the proposed technique and commands in python programming for the proposed energy data for the generation and clusters node, there are several four types of results are obtained to check the stability of the proposed data and whole electrical system.

To check the stability of each node, the proposed algorithm is implemented, and Figure 3-4 and Figure 3-5 is showing the stability of generation node. In which it's showing that the density of power is not constant according to interval, which means generation is varying with respect to time.

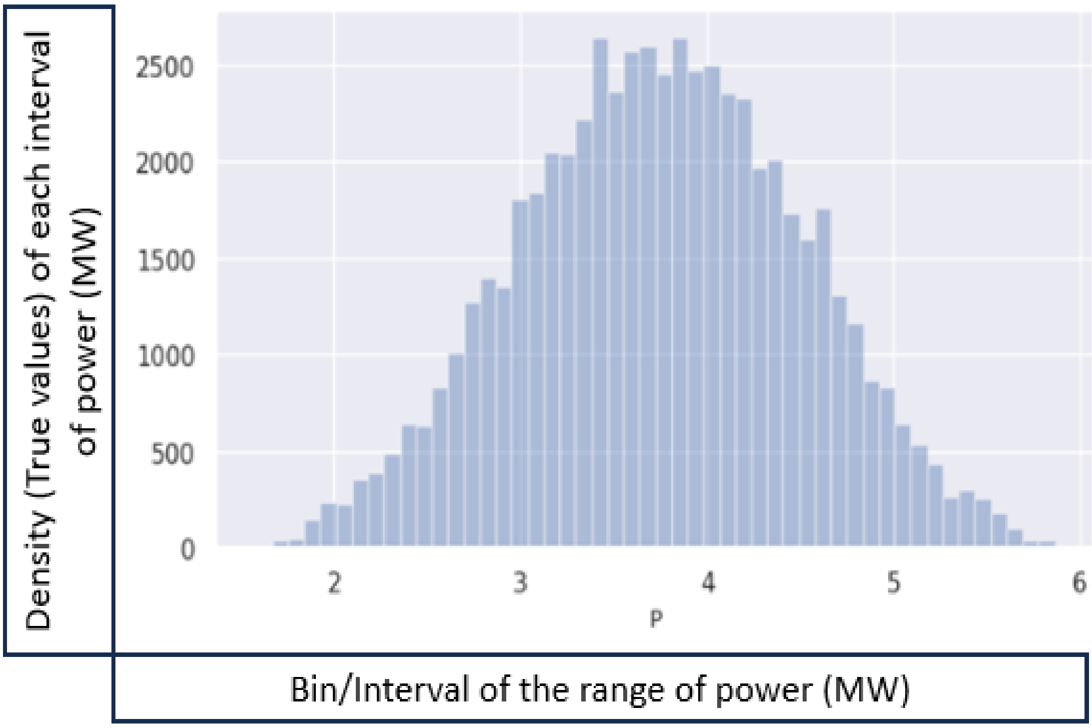



Figure 3-4: Stability of the generation node (Displot)

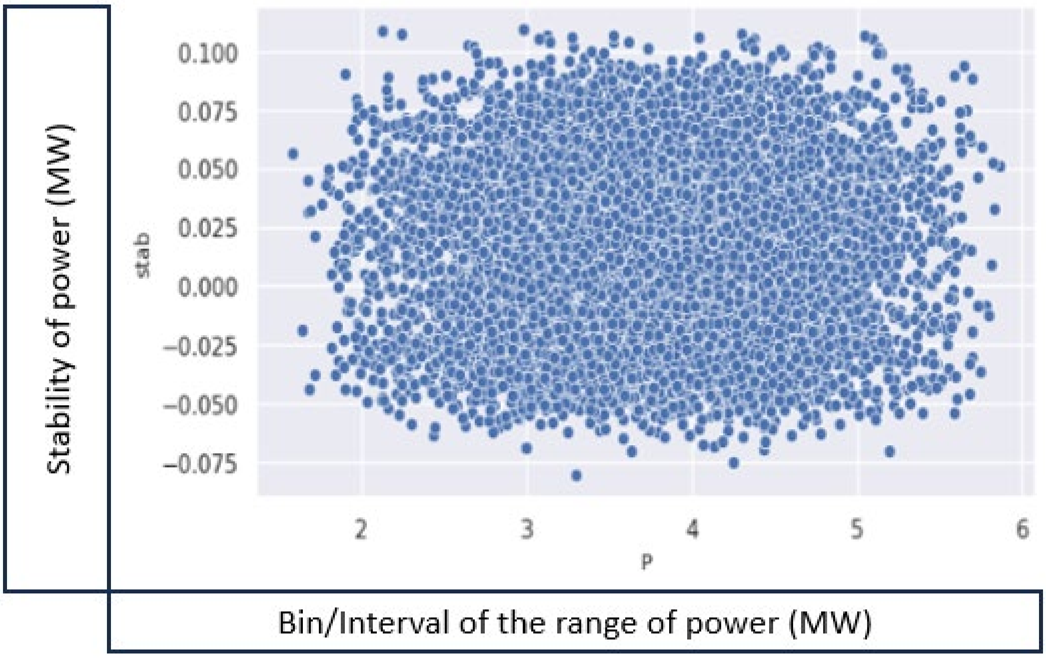



Figure 3-5: Stability of the generation node (Hisplot)

In Figure 3-6, there are the results of stability for cluster-1, cluster-2, and cluster-3, which showing that, in all these plots the stability is constant at the all clusters side, which means the overall demand is constant according to the requirements of customers either consumers or prosumers. The main generation is varying according to the demand that's why at generation side stability is not constant instead of clusters and customer's side.

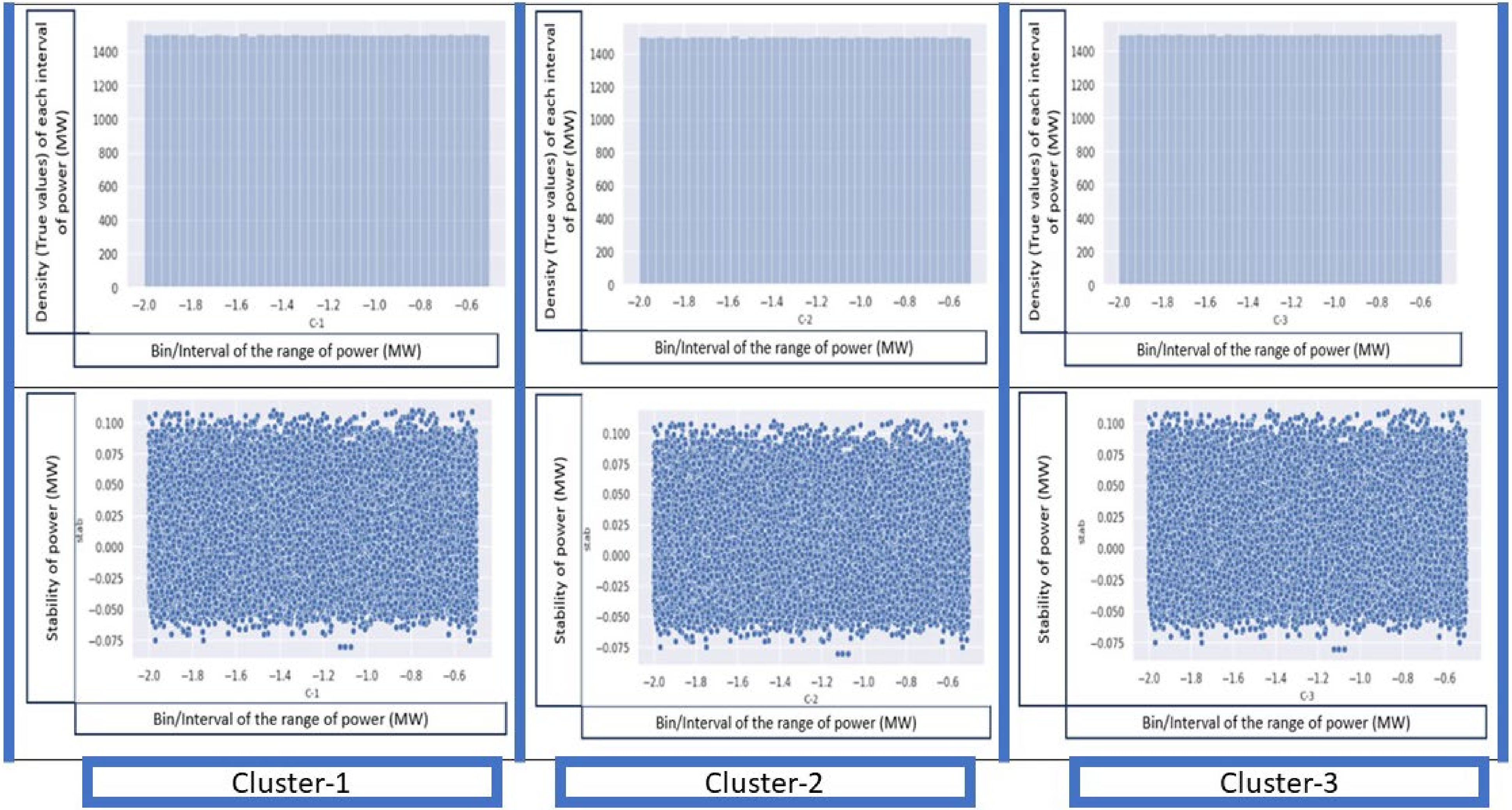



Figure 3-6: Stability of Cluster-1, Cluster-2, and Cluster-3 (Displot and Hisplot)

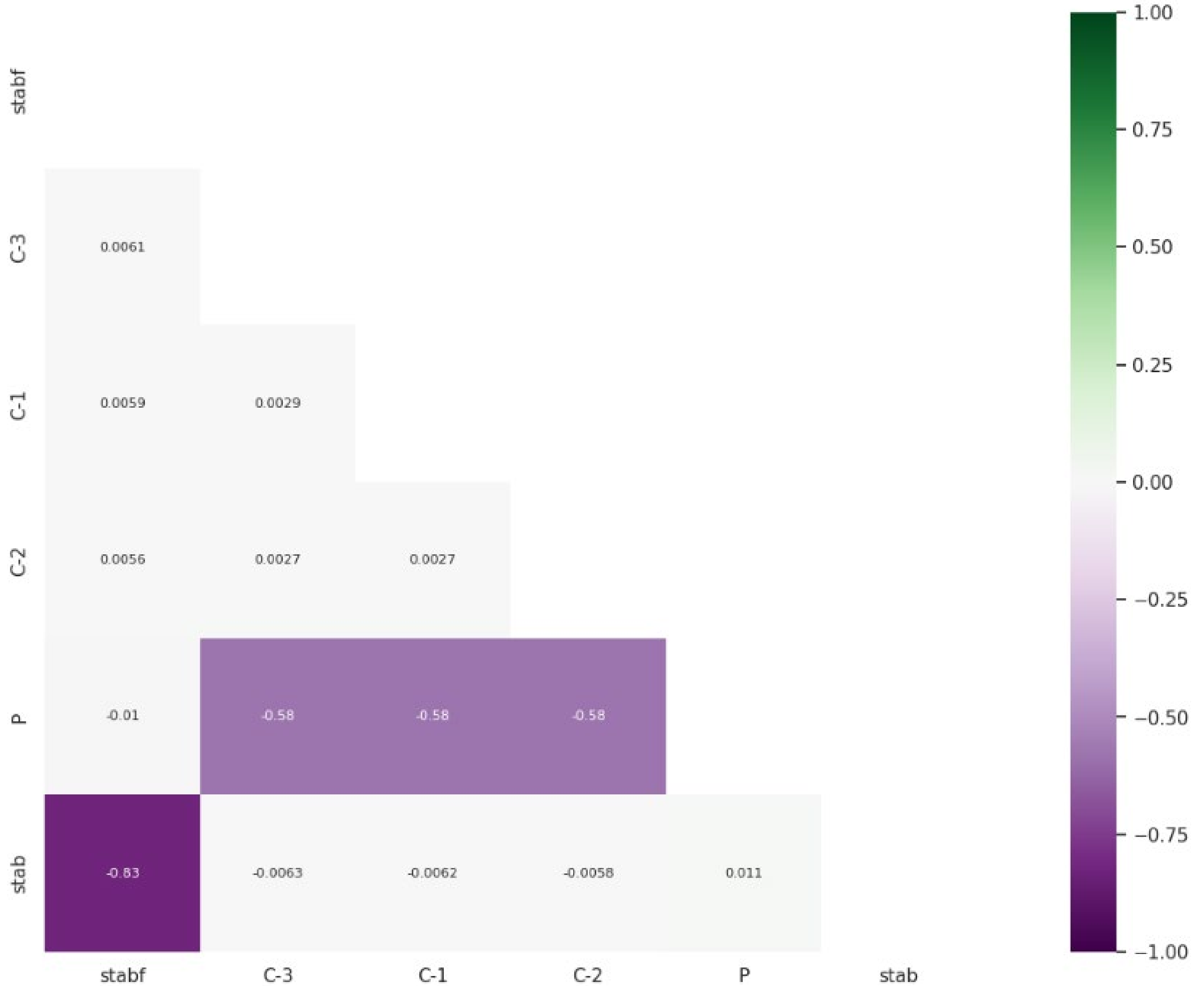



*Figure 3-7:* Correlation Matrix of the proposed technique and data

At clusters side for the proposed implementations, all these plots in Figure 3-6 showing that, the values of the proposed datasets are more stable at clusters side instead of the generation node, which is varying according to required demand.

The correlation matrix in Figure 3-7, is a data visualization to represent the correlation of variables of energy dataset. In correlation matrix, it's verifying from the values that if positive variable values of the proposed datasets are increases, then the negatives variable values should also be increased with the same rate for the strong correlation, and on right side bar in correlation matrix it's clearly showing that zero is in the middle of the positive and negative values, so it's clearly showing that this correlation matrix is correct for the proposed technique and proposed energy dataset.

## 3.3 Data Implementation Steps in DNN

The main part of DSEM is an implementation of data, there are several steps showing below, which are considered for the implementation of data. *Figure 3-8*,

1. Literature review on DSEM techniques in SG.
2. Collection of comprehensive datasets for DSEM.
3. Developing DNN based model for DSEM.
4. Implementation of developed model on all clusters.
5. Training, Testing and evaluation of developed model.
6. Comparison with existing techniques.

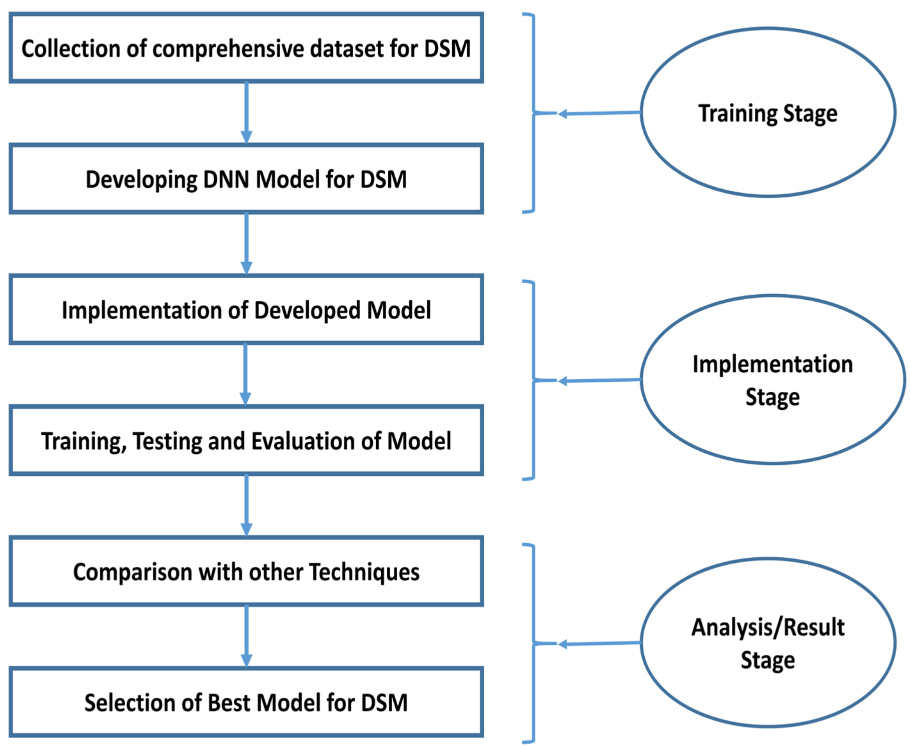



Figure 3-8: Data Implementation steps for DSEM

### 3.3.1 Data Collection for DNN Implementation

The historical data can be collected from repositories where scientists have already stored data for research purposes such as GitHub, ResearchGate, etc. The advantage of working on the already posted datasets is that, the efficiency of proposed algorithm can be compared the with the previous results. Data can also be collected by obtaining the readings of required parameters (current, voltage, etc), at different sources and load ratings. After collecting the required dataset, it is possible to use it for the training, validation and testing steps of DNN for the required output results, such as prediction, detection and optimisation, as shown in the algorithm of Figure 3-9.

Neural networks can be a powerful tool for smart meter data collection at both consumers and prosumers' sides.

At the consumer side, neural networks can be used to analyse smart meter data to detect trends and patterns in energy consumption. This statistics can be used to optimise energy usage and reduce waste. For example, a neural network can be trained to identify peak energy usage times, and suggest ways to shift energy usage to non-peak times.

At the prosumer side, neural networks can be used to predict energy production from renewable sources such as solar panels. This information can then be used to optimise energy usage and sell excess energy back to the grid. For example, a neural network could be trained to predict solar panel output based on weather conditions and time during a day, and then suggest when to use energy and when to sell it back to the grid.

Overall, neural networks can provide valuable insights into energy usage and production, allowing consumers and prosumers to make more informed decisions about their energy consumption and production. However, it's important to ensure that data privacy and security are taken into account when implementing smart meter data collection systems.

Smart meters play a crucial role in the functioning of smart grids. A smart grid is an advanced electrical grid that uses modern communication and control technologies to manage the flow of electricity from generation to consumption. Smart meters are key components of smart grids because they enable two-way communication between consumers and the grid, providing real-time data on energy consumption and production. Smart meters are able to collect data on energy usage at regular intervals, typically every 15 minutes, and send this data back to the utility company through a communication network. This data can be used by the utility company to optimise energy distribution, manage peak demand, and detect and respond to power outages more quickly (LJ Lepolesa, S Achari, 2022).

In addition to enabling two-way communication between consumers and the grid, smart meters also allow for more flexible pricing models. With traditional metering systems, consumers pay a fixed rate for their energy usage regardless of when they use it. However, with smart meters, utilities can implement time-of-use pricing models that encourage consumers to shift their energy usage to non-peak times, when energy is cheaper and the grid is under less stress (MW Mufana, A Ibrahim, 2022).

Overall, smart meters are a critical component of modern smart grids, providing real-time data and enabling more efficient energy distribution and consumption.

Neural networks can be used for data collection from smart meters at the consumer's side. Smart meters are electronic devices that measure and record electricity usage in real-time. They are becoming increasingly popular as they enable better monitoring of energy usage, and help consumers to reduce their energy bills.

Neural networks are a type of machine learning algorithm that are designed to recognize patterns in data. They are particularly useful for processing large amounts of data, making them well-suited for analyzing the vast amounts of data generated by smart meters.

Here are some ways that neural networks can be used for data collection from smart meters at the consumer's side:

1. Load Forecasting: Neural networks can be used to predict future energy consumption based on historical usage patterns. This can help consumers to plan their energy usage more efficiently, and also help utility companies to optimise their energy generation and distribution.
2. Anomaly Detection: Neural networks can be used to identify unusual or abnormal energy consumption patterns, which could indicate equipment malfunctions, theft or fraud. This can help utility companies to identify and address potential issues before they become a major problem.
3. Demand Response: Neural networks can be used to identify peak demand periods, and incentivize consumers to reduce their energy usage during these periods. This can help to reduce the strain on the energy grid during times of high demand.

Neural networks can be a powerful tool for collecting and analyzing data from smart meters at the consumer's side. By providing insights into energy usage patterns, they can help consumers to make more informed decisions about their energy consumption, and also help utility companies to optimise their energy generation and distribution.

Smart meter real-time data monitoring is a process of continuously monitoring and analyzing the data generated by smart meters in real-time. Smart meters are electronic devices that measure and record energy consumption at regular intervals and transmit this data to the utility company for billing and analysis.

Real-time data monitoring of smart meters can provide a wide range of benefits, including:

1. Accurate billing: Real-time data monitoring of smart meters ensures accurate billing by providing up-to-date information about energy usage.
2. Energy efficiency: By providing real-time information about energy consumption, smart meters can help consumers to identify areas where they can reduce energy usage and save money.
3. Load management: Real-time data monitoring of smart meters can help utility companies to manage peak demand periods by identifying high consumption areas and incentivizing consumers to reduce energy usage during these periods.
4. Outage detection: Real-time data monitoring of smart meters can help to quickly identify power outages and enable utility companies to restore power more quickly.

To perform real-time data monitoring of smart meters, utility companies typically use advanced software systems that are capable of processing large volumes of data in real-time. These systems use algorithms and machine learning techniques to analyse the data and provide insights into energy usage patterns, peak demand periods, and potential issues such as equipment malfunctions or theft.

Overall, smart meter real-time data monitoring is an important tool for improving energy efficiency, managing peak demand periods, and ensuring accurate billing. By providing consumers and utility companies with up-to-date information about energy usage, it can help to reduce energy costs, improve reliability, and promote sustainable energy use.

It is assumed that every consumer/prosumer connected to the Smart Grid will have a smart meter, this will enable all the necessary data to be collected. These smart meters have the capacity to record the details of consumers' consumption of electricity. Once, the consumers a smart meter installed, it has the capacity to communicate directly with providers and data hubs to send the data about:

a. How much energy the consumers are using
b. When they are using it

Smart meters have the capacity to record the consumer's energy in real-time. They do this by measuring gas and electricity flow at regular intervals of time. This consumption data is then sent directly to the energy suppliers. Smart meters communicate with energy suppliers and hubs through the WAN (wide area network). It is the same as the network used by mobile phones. Meter data is collected frequently to get real-time electricity information from suppliers to the consumer side.

**The collection of data has the following benefits.**

a. Accurate electricity bill
b. Energy supply management
c. Accurate forecast of energy
d. Energy efficiency advice
e. To make sure the better customer services
f. Implementation of Smart-Grid to reduce the pressure of energy on National-Grid

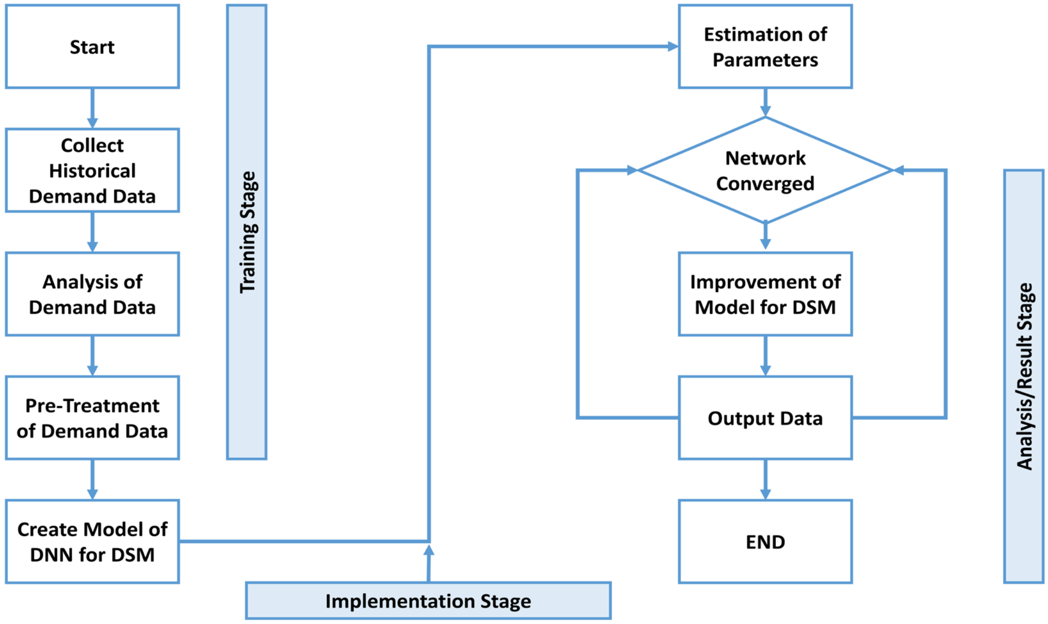



Figure 3-9: Algorithm for DSEM in SG (Savani 2018)

### 3.3.2 Structure and Testing of Data by Implementing the DNN

Deep Neural Network (DNN) have different approaches which includes AI (Artificial Intelligence) to CI (Computational Intelligence) for intelligent control of DSEM as shown in Figure 3-10. DNNs have three categories of layers, namely, Input, Hidden and Output for the testing and training of data to achieve the desired results. The number of hidden layers is modified to suit the accuracy of the required result/prediction as shown in Figure 3-11. To optimise the entire network, DNN is implemented to achieve the desired optimised energy management results of output in more accurate and secure way, the generalize algorithm of DNN is shown in Figure 3-12.

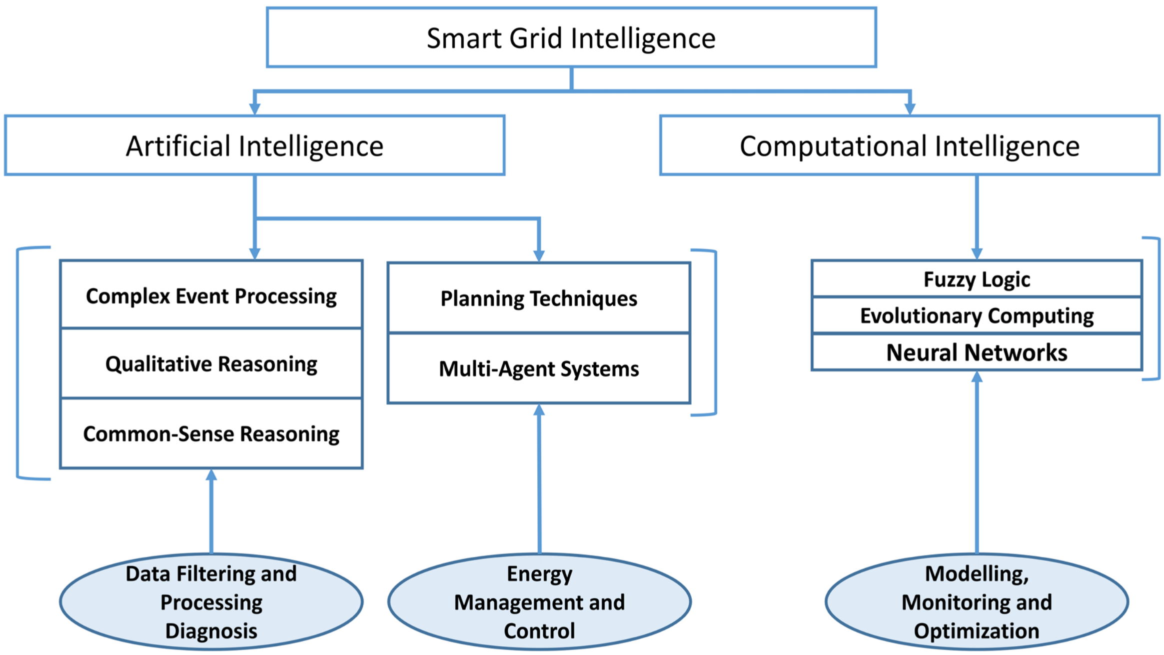



Figure 3-10: ML Implementation for DSEM (Samadi et al 2012)

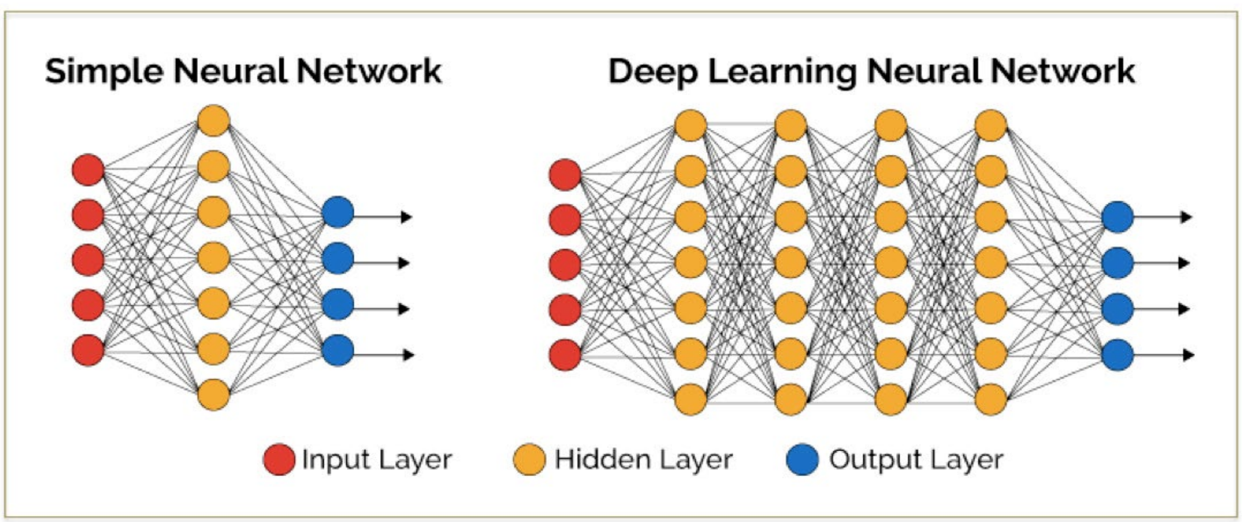



Figure 3-11: DNN Multi-Layers (Bae et al. 2014)

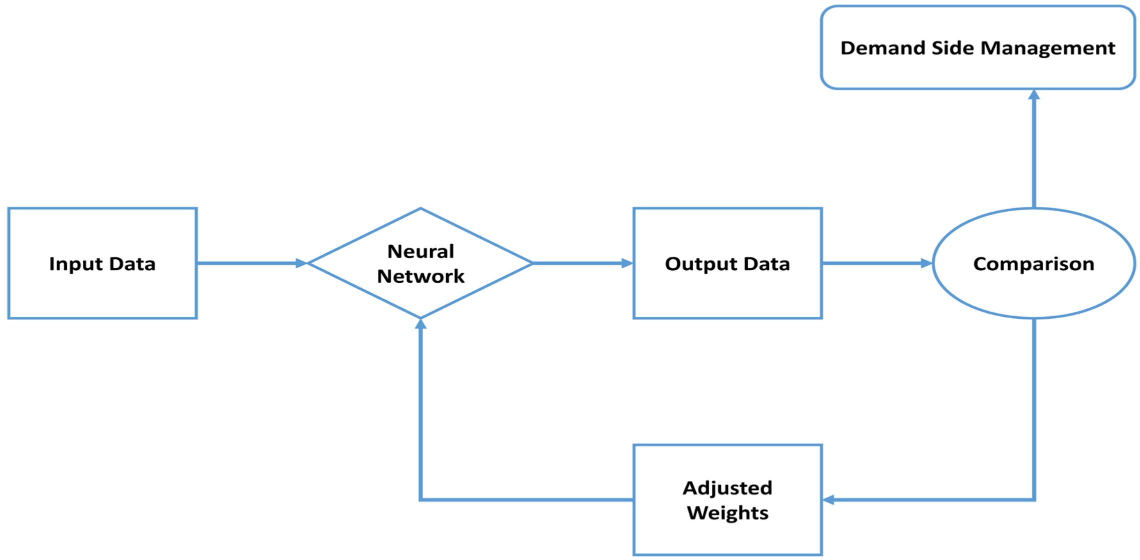



Figure 3-12: DNN Algorithm to Implement  for DSEM

### 3.3.3 Methodologies and Procedures of DNN

There are various stages of DNN implementation for DSEM in SG.

Initially, full dataset is required for demand of providers to customers' side to implement it on DNN algorithm, the algorithm will not run properly if any value in the dataset is missing or false.

Secondly, after collection of full datasets, DNN model is required with best optimiser to operate it.

Thirdly there is a need of operation which consists of the following three stages,

- **Training stage**: In this stage, DNN start processing and experiences based on collected input dataset and stores the possible outcomes of data.
- **Validation stage:** In this stage, some different parameters are used to tune the classifiers, such as to choose the number of hidden layer units in a neural network.
- **Testing stage**: As its name identifies that, it is a testing stage at which DNN algorithm will test the data and achieve the possible outcomes from the input data after its processing in input layer to hidden layers and then output layer shows our possible and desired output.

Finally, there is a comparison of output result by the dataset implementation on various approaches with different optimisers. By implementing DNN approach at various clusters the DSEM in SG can be control and monitor to manage the entire system more reliable, secure, and efficient. The overall classification stages of DNN implementation is shown in Figure 3-13.

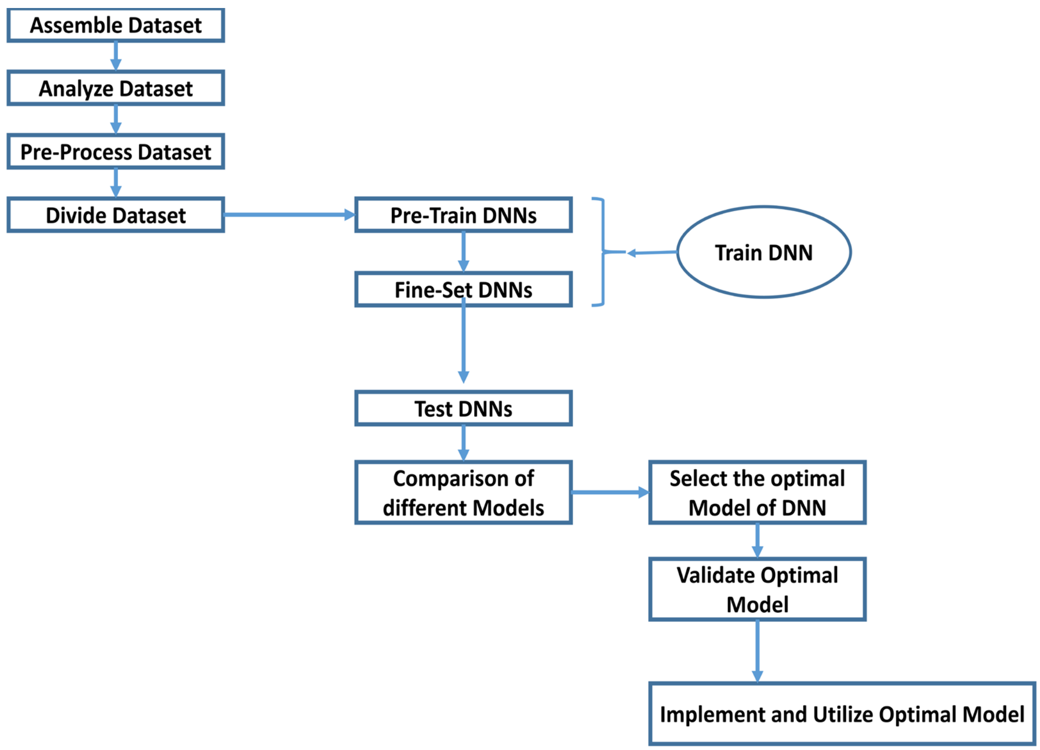



Figure 3-13: Classification of Stages by Implementing DNN

### 3.3.4 Mathematical Explanation of DNN Implementation

The overall neural network characterisation of layers is shown in Figure 3-14, and step by step describes below.

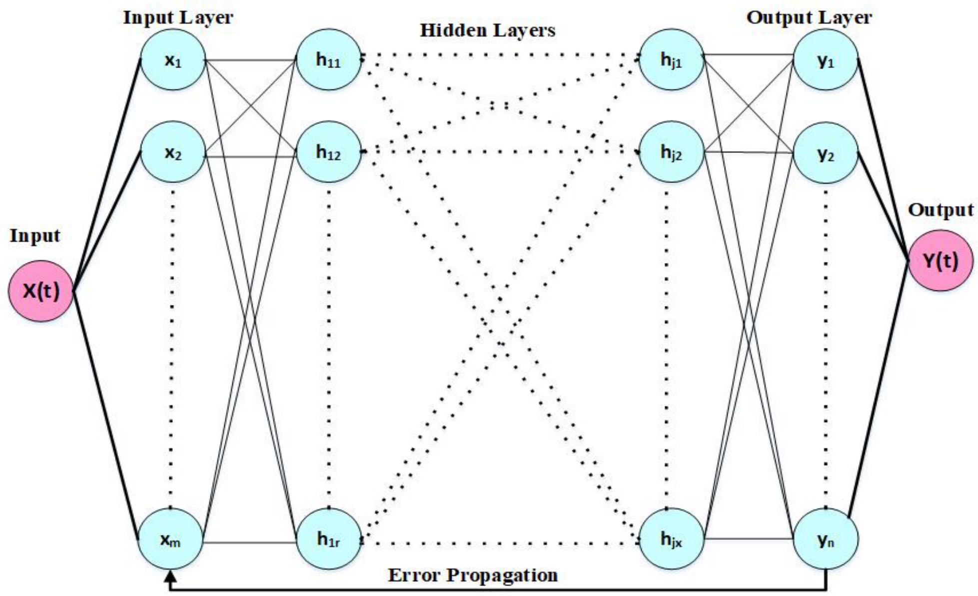



Figure 3-14: Deep Neural Network Layers Characterisation

Equation-3.1 can be used to characterise the overall model of a neural network.

$$Y[t] = X[t] * W[t] + G \tag{3.1}$$

Where $\boldsymbol{Y}$ represents the output, and $\boldsymbol{X}$ represent the input values, $\boldsymbol{W}$ represents all connected weights and $\boldsymbol{G}$ is the activation function, that is used to combine the weights and concluded results sent to output ($\boldsymbol{Y}$).

Let $\boldsymbol{X}$ be the input to the input layer and this can be represented by equation-3.2

$$X[t] = x_1, x_2, x_3 \dots \dots \dots x_m \tag{3.1}$$

Where $\boldsymbol{x_1, x_2, x_3} \dots \dots \dots \boldsymbol{x_m}$ represents the input values from $\boldsymbol{1}$ to $\boldsymbol{m}$.

Let the weights of the links in each hidden layer be $\boldsymbol{W}$ for the training, can then be represented in equation-3.3

$$W = W_{12}, W_{23}, \dots \dots \dots W_{(j-1)j} \tag{2.3}$$

The Deep Neural Network (DNN) weight matrix is represented by $\boldsymbol{W}$ and the vectors of weight for $\boldsymbol{j}$ layers are represent by $\boldsymbol{W_1, W_2, W_3} \dots \dots \dots \boldsymbol{W_j}$. Equation-3.4, represents the weight vector of the first layer.

$$W_{12} = w_1, w_2, w_3 \dots \dots \dots w_j \tag{3.3}$$

In a linear equation the intercept is represented as the Bias (B), it is an additional parameter in the DNN which is used to adjust the output along with the weighted sum of the inputs to the neuron. The bias B is shown in equation-3.5 for j hidden layers.

$$B = B_{12}, B_{23}, \dots \dots \dots B_{(j-1)j} \tag{3.4}$$

The bias vector value for the first hidden layer is given by $B_1$ and is shown in equation-3.6.

$$B_{12} = b_1, b_2, b_3 \dots \dots \dots b_r \tag{3.5}$$

The net input value of j hidden layers is represented by Z in equation-3.7, for n layers in the neural network.

$$Z = Z_1, Z_2, Z_3 \dots \dots \dots Z_j \tag{3.6}$$

For the first hidden layer the value of Z is showing in equation-3.8.

$$Z_1 = B_{12} + \sum [X[t] * W_{12}] \tag{3.7}$$

Equation-3.9, illustrates that A is the activation value of function for all individual layers, which is used to propagate the total loss back in deep neural network, which is generally called back-propagation error.

$$A = A_1, A_2, A_3 \dots \dots \dots A_j \tag{3.8}$$

Where $\boldsymbol{A_1, A_2, A_3} \dots \dots \dots \boldsymbol{A_n}$ the activation are functions of each hidden layer and can be represented as equation-3.10.

$$A_1 = \frac{1}{1 - e^{-Z_1}} \tag{3.9}$$

In equation-3.11 the function of $\boldsymbol{Q}$ to find the values of overall output layers.

$$Q_n = B_n + \sum (A * W_n) \tag{3.10}$$

The activation function $\boldsymbol{f}\ (\boldsymbol{Q})$ is applied at the output layer and input layer to is used to calculate the overall value of the combined output $\boldsymbol{Y}$, this is shown in equation-3.12

$$Y = f\ (Q) \tag{3.12}$$

The mean square error **(*MSE*)** of entire network is calculated in equation-3.13, where $Y_f$ is the final desired output and $Y_i$ is the neural network output, where $n$ is the number of output nodes.

$$MSE = \frac{1}{2n}\sum_{i}^{n}(Y_f - Y_i)^2 \tag{3.13}$$

The above outcome of the output ***Y*** can be compared with possible results, then the error, ***E*** can be calculated as follows in equation-3.14.

$$E = T - Y \tag{3.14}$$

To achieve the desired output, the convergence value can be determined using equation-3.15 to minimize error values. A deep neural network model reaches convergence when, during training, its loss stabilizes within a defined error range around the final value, indicating that further training will not improve the model. Backpropagation, short for "backward propagation of errors," is a common method for training deep neural networks. It calculates the gradient of the loss function with respect to all network weights, facilitating adjustments that enhance model performance.

$$E[1] = (T[1] - Y[1])f'(Q[1]) \tag{3.15}$$

Equation-3.16 represents the change in weight of all hidden layers for required output values.

$$W_c(1) = \alpha * E(1) * A \tag{3.16}$$

During the training of a neural network, the change in output bias outcomes is represented in equation-3.17.

$$B_c(1) = \alpha * E(1) \tag{3.17}$$

By using equation-3.18 the hidden layer error values can be calculated.

$$Z'(n) = \sum (E(1) * W\ (n)) \tag{3.18}$$

Where ***E*** is the function to find the possible error values in hidden layers, which is represented in equation-3.19.

$$E(2) = Z(n) * f'(Z(n)) \tag{3.19}$$

The modification in possible weight values in hidden layers can be considered as shown in equation-3.20.

$$W_c(2) = \alpha * E(2) * Z(n) \tag{3.20}$$

Similarly, the change in bias values can be determine using the following equation-3.21

$$B_c(2) = \alpha * E(2) \tag{3.21}$$

When the optimisation technique is implemented then new bias values can determine by equation-3.22

$$W'_n(1) = W(2) * W_c(1) \tag{3.22}$$

The updated value of bias can determine using equation-3.23 after running the optimisation technique.

$$B'_n(1) = B(2) * B_c(1) \tag{3.23}$$

The weight values and the bias values can be updated in the hidden layers by using equations-3.24 and 3.25.

$$W'_n(2) = W(1) * W_c(2) \tag{3.24}$$

And

$$B'_n(2) = B(1) * B_c(2) \tag{3.25}$$

Data management is very essential task for developing the overall model and implement it for required outcomes of energy. There are three stages for collecting the data and its implementation for training, validation, and testing stage. However, full dataset is required to achieve the required and perfect outcomes, but if dataset is missing some values, then there will be some delays and errors in required outcomes as shown in Figure 3-15.

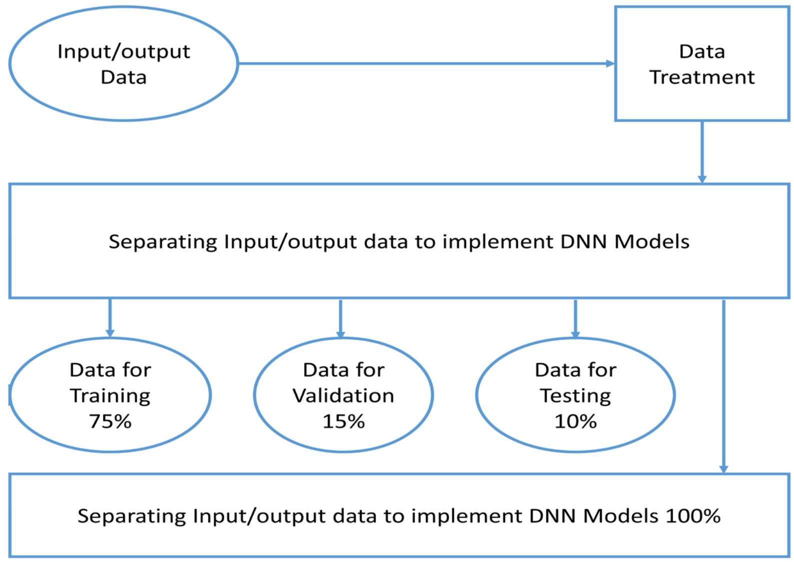



Figure 3-15: Data Management by DNN in SG

## 3.4 Significance of DNN for Energy Management in Electrical Systems

Deep Neural Networks (DNN) are widely used in the different fields from medicine treatment, Physical sciences, and engineering problems. It can be used for demand side energy management as well, due to the following reasons it is most significance as compared to other techniques.

1. Deep neural networks are created to digitally mimic the human brain.
2. Deep neural networks learn events and make decisions by commenting on similar events.
3. Deep neural networks have numerical strength that can perform more than one job at the same time.
4. Deep neural networks have the capacity to learn from examples and apply this knowledge when encountering similar situations, enabling them to handle real-time events effectively.
5. Additionally, even if a neuron fails to respond or certain information is missing, the network can identify the fault and continue to generate an output.

6. The primary advantage of using Deep Neural Networks (DNNs) is their ability to manage large datasets while implicitly detecting complex, nonlinear relationships between dependent and independent variables.
7. Deep neural networks can detect all possible interactions between predictor variables.
8. Deep neural networks are good for Pattern Recognition, Classification and Optimisation.
9. With multiple layers, deep neural networks become more adept at learning complex features and handling intensive computational tasks, enabling them to execute numerous intricate operations concurrently.
10. Clarification is the most important advantage of neural networks to predict the possible outcomes.

## 3.5 Voltage regulation in Electrical Systems by implementing the technique of DNN and it's comparison with PID Controller

By considering the synchronous generator, having electromagnetic torque Te and driving mechanical torque Tm , Under steady state conditions by neglecting the losses, these both torque have the following equal relation.

$$\mathrm{T}e = \mathrm{T}m \tag{3.26}$$

If the situation is not steady state, then the torque on the rotor $T_a$ have the following relation.

$$\mathrm{T}a = \mathrm{T}e - \mathrm{T}m \tag{3.27}$$

If J is the combined moment of inertia of the generator and prime mover by neglecting the frictional and damping torques, there is a relation

$$\mathrm{J}\frac{d^2\theta_m}{dt^2} = \mathrm{T}a = \mathrm{T}e - \mathrm{T}m \tag{3.28}$$

Where $\theta_m$ is the angular displacement of the rotor, where $\delta_m$ is the rotor position.

$$\theta_m = \omega_{syn}t + \delta_m \tag{3.29}$$

And the rotor acceleration is

$$\frac{d^2\theta_m}{dt^2} = \frac{d^2\delta_m}{dt^2} \tag{3.30}$$

From equation (3) and (5)

$$J\frac{d^2\delta_m}{dt^2} = Tm - Te \quad (3.31)$$

Multiplying both sides with $\omega_m$

$$J\omega_m\frac{d^2\delta_m}{dt^2} = \omega_m(Tm - Te) \quad (3.32)$$

Since angular velocity times torque is equal to the power.

$$J\omega_m\frac{d^2\delta_m}{dt^2} = Pm - Pe \quad (3.33)$$

The quantity $J\omega_m$ is called the inertia constant and it is denoted by $M$. It s related to the kinetic energy of the rotating masses $W_k$.

$$W_k = \frac{1}{2}J\omega_m 2 = \frac{1}{2}M\omega_m$$

$$\text{Or} \qquad M = \frac{2W_k}{\omega_m} \quad (3.34)$$

And at the synchronous speed of the rotor, the above equation can be write as,

$$M = \frac{2W_k}{\omega_{syn}} \quad (3.35)$$

The swing equation in terms of inertia constant can be write as,

$$M\frac{d^2\delta_m}{dt^2} = Pm - Pe \quad (3.36)$$

H is the constant or per unit constant, which can be define as,

$$H = \frac{Kinetic\ Energy\ in\ MJ\ at\ rated\ speed}{Machine\ rating\ in\ MVA} \quad (3.37)$$

The swing equation can be write in terms of per unit as,

$$\frac{H}{\pi f_0}\frac{d^2\delta_m}{dt^2} = Pm - Pe \quad (3.38)$$

If $\delta$ is expressed in electrical degrees, so the swing equation can be write as,

$$\frac{H}{180 f_0}\frac{d^2\delta}{dt^2} = Pm - Pe \quad (3.39)$$

The overall block diagrams of generator model, generator and load model, and steam turbine model after implementing the above equations for transfer functions are shown in Figure 3-16, Figure 3-17, and Figure 3-18, respectively.

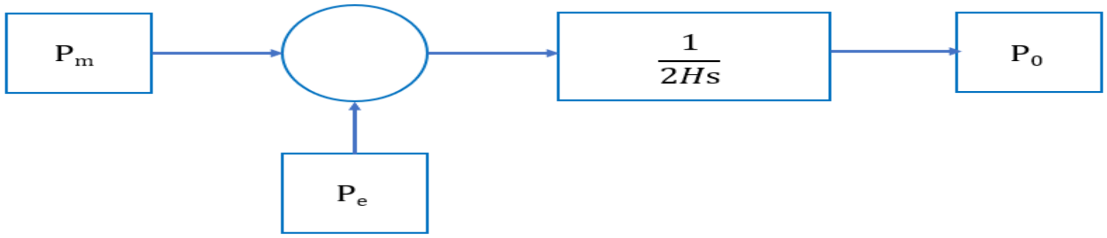



Figure 3-16: Generator Model Block Diagram

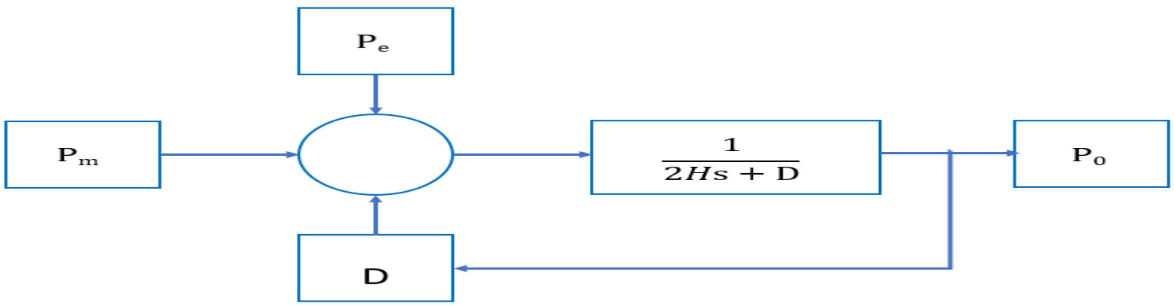



Figure 3-17: Generator and Load Block Diagram

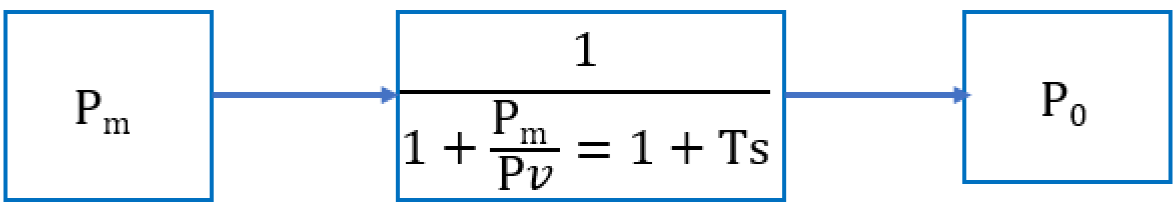



Figure 3-18: Steam Turbine Block Diagram

For the implementation of DNN on any electrical system, firstly there is a need to design the system with the required parameters. In Figure 3-19, there is an electrical system, in which there is an amplification of the generator voltages is held. However, the purpose is that the output voltages should be stable, to achieve the stable output there is a need of controller, which controls the output at terminal end. For these purposes the electrical system is design as shown in Figure 3-20, by using the PID and NN controllers. In Figure 3-21, and Figure 3-22, there is an output graph by using the PID and Neural Network controller, respectively, which shows that by using the NN controller voltages after a 3 sec becomes stable, however the result of PID controller showing that after a 30 sec voltages are still varying and unstable.

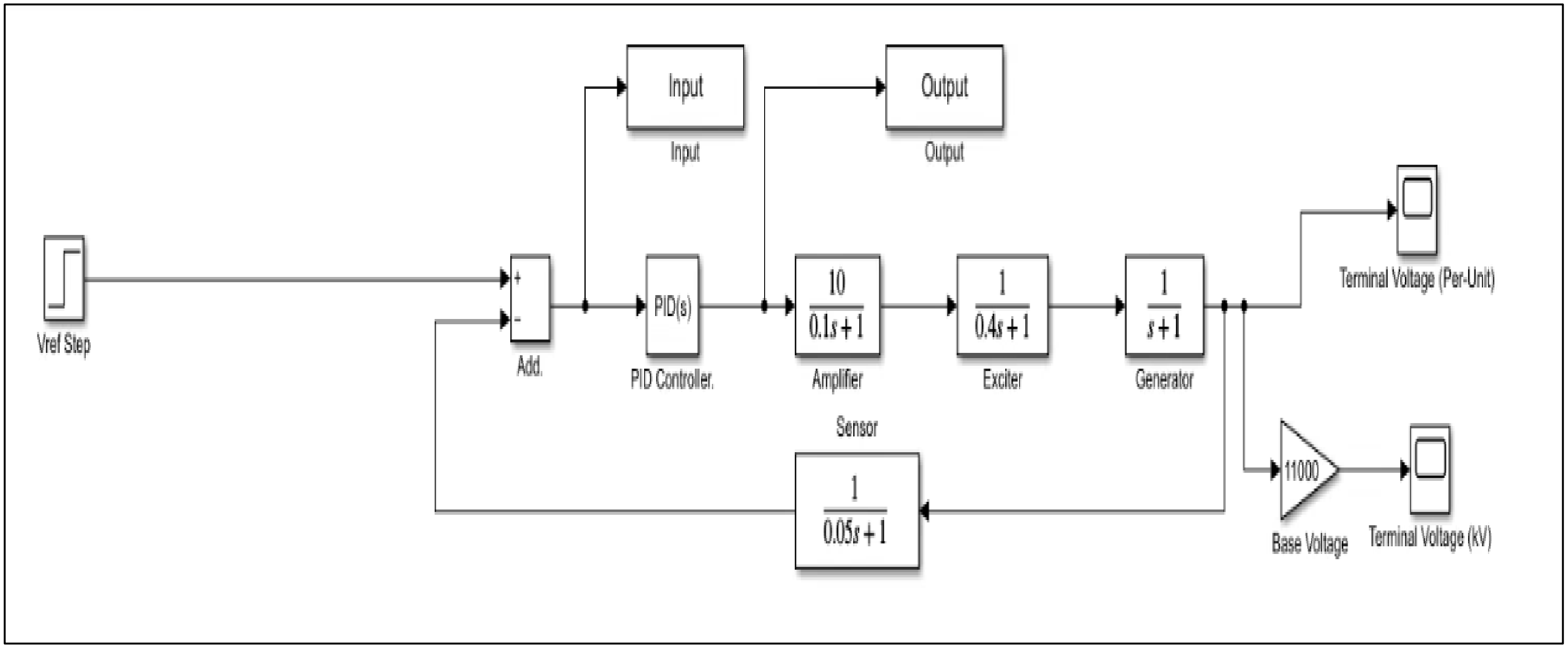



Figure 3-19: Voltage Amplification System at output by using PID Controller

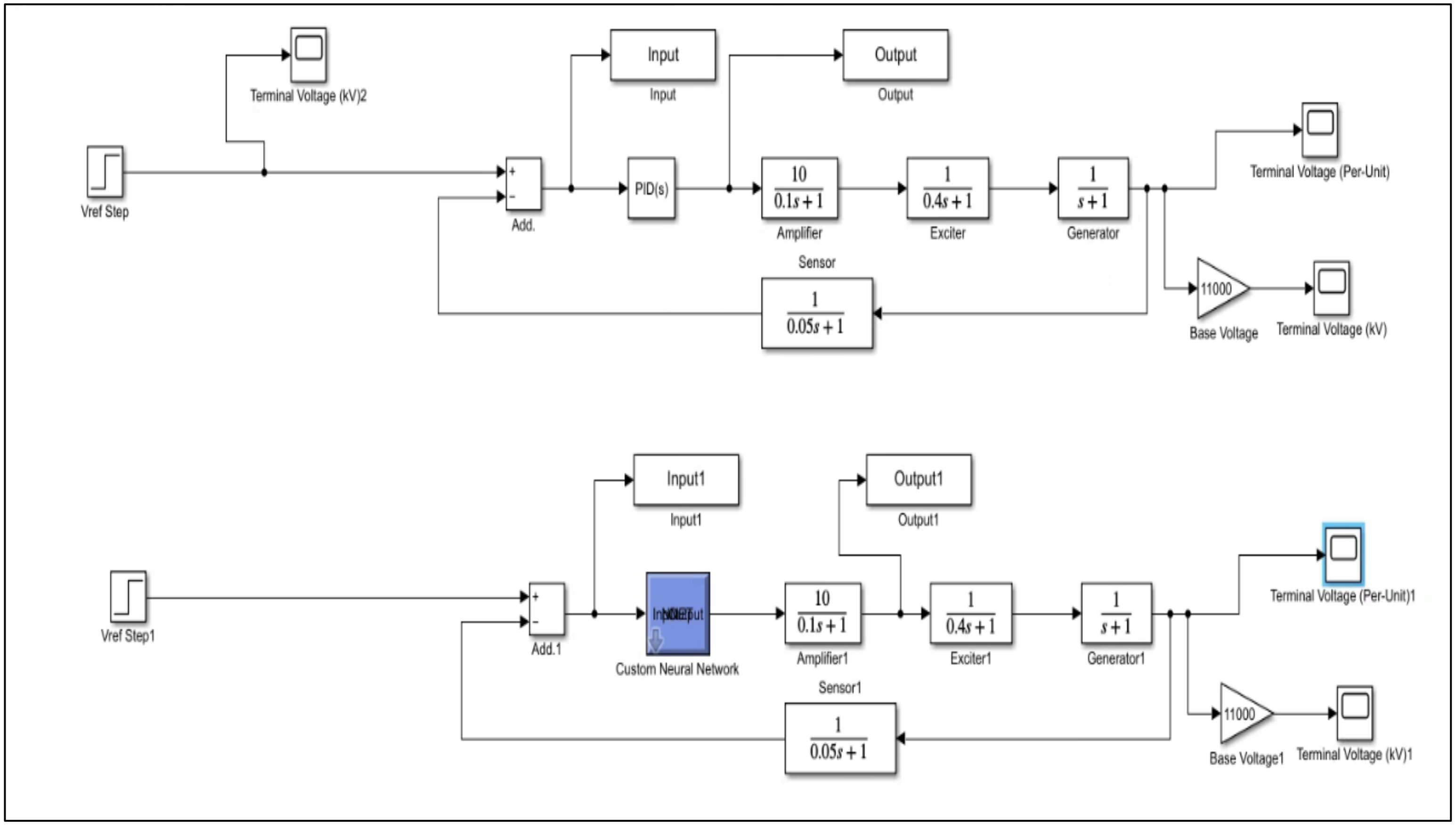



Figure 3-20: Voltage Amplification System at output by using Neural Network Controller

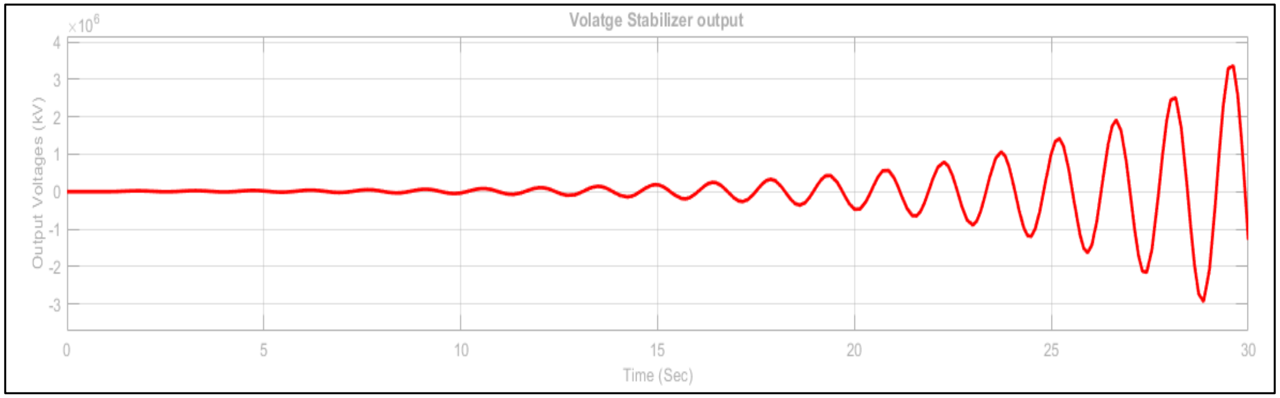



Figure 3-21: Output voltages using PID Controller

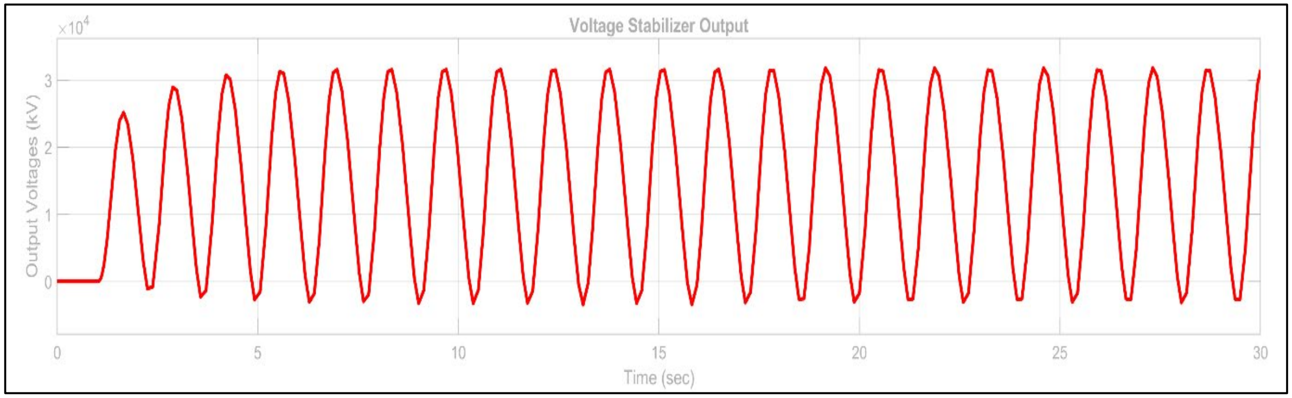



Figure 3-22: Output voltages using ANN controller

## 3.6 Frequency regulation in Electrical Systems by implementing the technique of DNN and it's comparison with PID Controller

To enhance the efficiency of energy at consumer side, it's also needed to stabilize the frequency at the consumer side or any output point. In Figure 3-23, there is an electrical model which is based on the transfer functions of the thermal and hydro power plants and shows that PID controller is used to control the output frequency. And in Figure 3-24, there is an output of frequency (Hz), which shows that after the tuned model of PID controller, it takes a long-time t (25sec) decreasing the magnitude of frequency and obviously it will take longer to become stable.

Now in Figure 3-25, PID controller is replaced with NN controller with same parameters of the remaining model, and ANN is attached after the successful training of the neural network by taking the input and output data of the system by using workspace block in simulation. In Figure 3-26, it's showing that after the third or fourth cycle the frequency of the model is stable at the output point.

From both two models and output curves, it's clearly observed that the performance of an ANN controller is efficient to stabilize the voltages, frequency or any other output at the consumer side. Because ANN working is artificial intelligence based which takes the input and output data to obtain the best training of the model based on the system parameters to achieve the best possible outcomes.

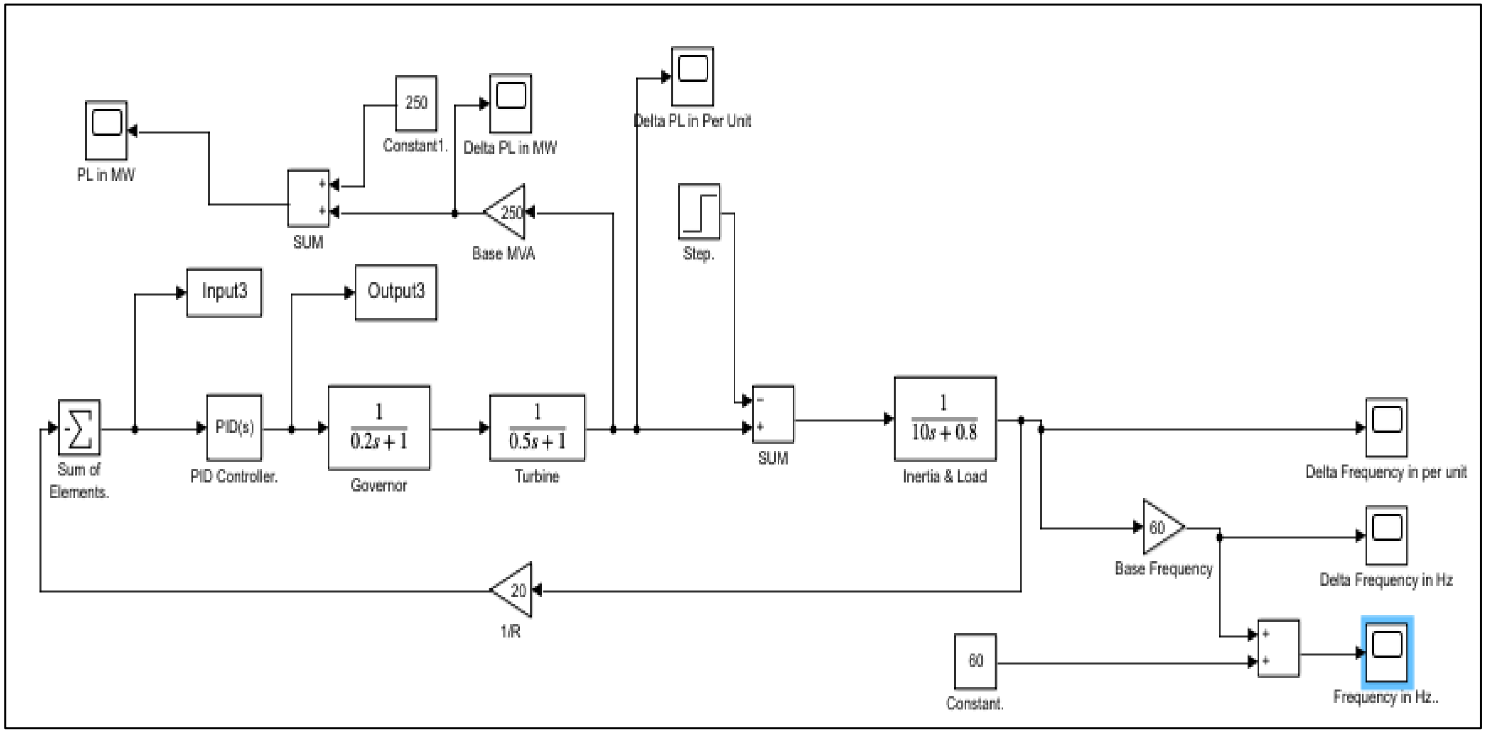



Figure 3-23: Load Frequency Control Model using PID controller

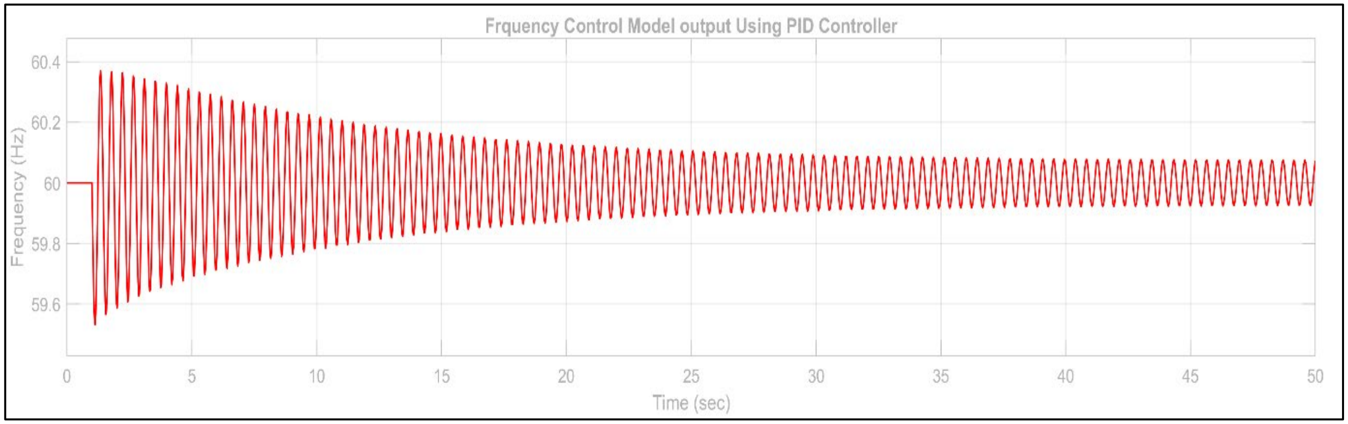



Figure 3-24: Output Frequency (Hz) with PID controller

Electrical system with ANN Controller is shown below in Figure 3-25.

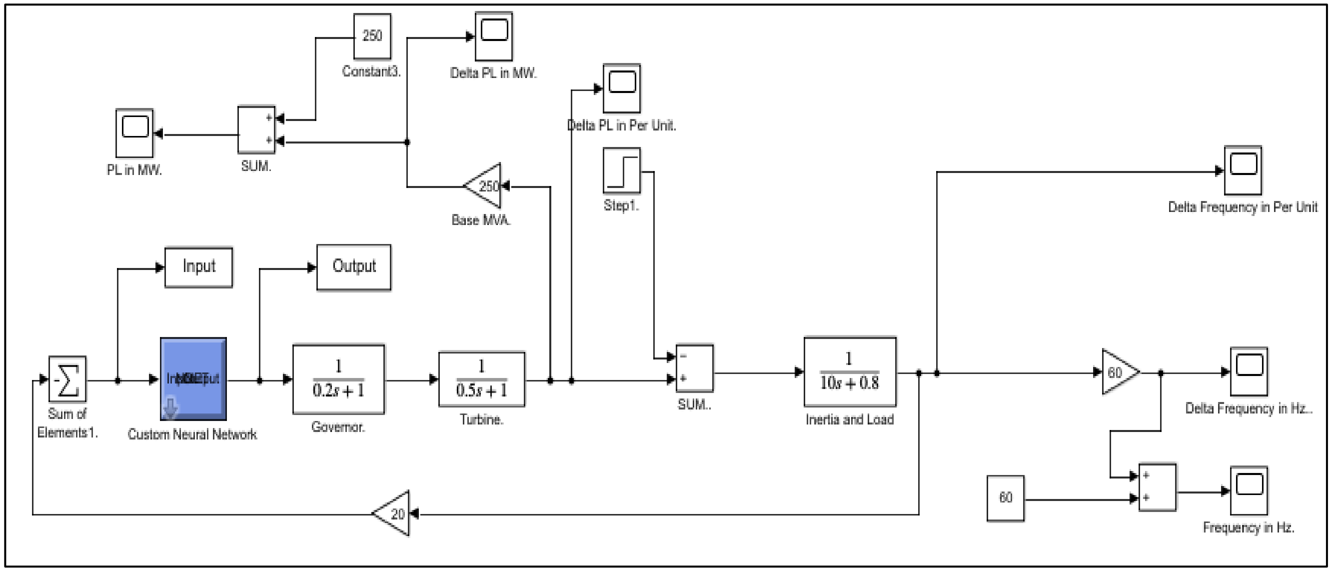



Figure 3-25: Load frequency Control Model using ANN Controller

Output result of Frequency (Hz) with ANN Controller is shown below in Figure 3-26.

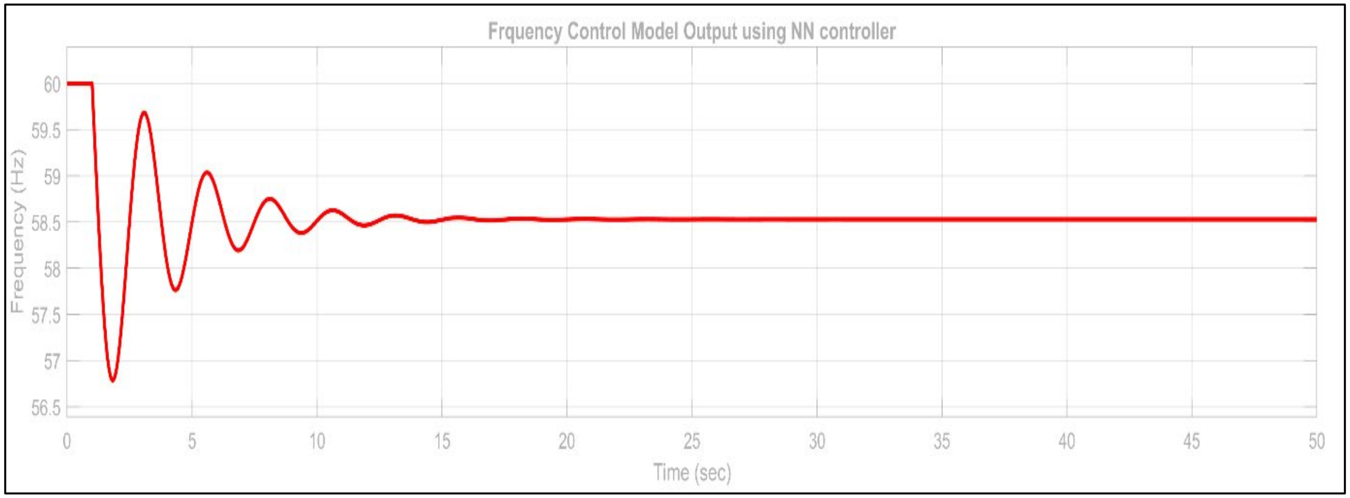



Figure 3-26: Output frequency using ANN Controller

In Figure 3-24 and Figure 3-26 there is a comparison of graphical output frequencies with PID and NN controller. However, Figure 3-23 and Figure 3-25 have an electrical model representation with PID and NN controller systems to stabilize the frequency at the output at a single point. The Figure 3-26 is shows that after 10 sec, the output frequency of the system with NN controller is stable at a single point of 58.5 Hz, however it's showing that with the PID controller it takes time to stabilize, even after 50 sec of the interval, its value is varying. That's why, NN controller have the capacity to change and optimise the system in aspects of load and frequency to optimise the system. The advantage of DNN is to automatically sampled the input (Providers, prosumers) data to achieve the optimised condition more quickly and accurately, as show in Figure 3-26.

Data sampling is an important aspect of training neural networks. It involves selecting a subset of data from a larger dataset to train the network on. There are different sampling methods that can be used in neural network training, including random sampling, stratified sampling, and balanced sampling.

1. Random sampling involves selecting data points randomly from the dataset. This method is simple and easy to implement, but it may not be ideal for datasets with class imbalance or where certain data points are more important than others.
2. Stratified sampling involves selecting data points based on their class distribution. This method ensures that each class is represented equally in the sampled data, which is important for datasets with class imbalance.
3. Balanced sampling involves selecting data points in a way that balances the number of samples from each class. This method is similar to stratified sampling but goes a step further to ensure that the number of samples from each class is equal.

In neural network training, it is important to use a sampling method that is appropriate for the dataset and the specific problem being addressed. The choice of sampling method can have a significant impact on the performance of the network, and it is therefore important to choose the most appropriate method for the task at hand.

## 3.7 Voltage and frequency regulation in Electrical Systems by implementing the technique of DNN and it's comparison with PID Controller

For the isolated power station, there is a need to control the voltage and frequency at output point in same time. In Figure 3-27, there is an isolated power model with PID controller, and in Figure 3-28, and Figure 3-29, there is an output waveform of frequency and voltage respectively. Which shows that after 50 seconds, there is no stable output, by using the PID controller. However, In Figure 3-30, the same power is controlled with neural network controller, and Figure 3-31 and Figure 3-32, represents that the output waveforms of frequency and voltage is at stable form, even after the 10 seconds approximately.

An isolated power systems has the following parameters, from Block diagram figures and swing equation, we drive the transfer functions of generator, governor, turbine and load, which are using in the isolated power system.

Turbine Time constant = Tt = 0.5 sec, Governor Time constant = 0.2 sec

Generator Inertia Constant = 5 sec

Governor Speed Regulation = 1/R = 1/0.05 = 20 per unit

Procedure and steps of implementation for the training and testing of data:

1. create a training sample input set,
2. Initialize the network with weight and bias values,
3. Read the set of data,
4. Create a training set and test set
5. Create Neural Network,
6. Net training of data set,
7. Output training and regression plot,
8. Set the minimum convergence error goal and performance function MSE (Mean Square Error) value,
9. Train the neural network net=train(net,I,T)(where I & T are parameters),
10. Check the root mean square error.

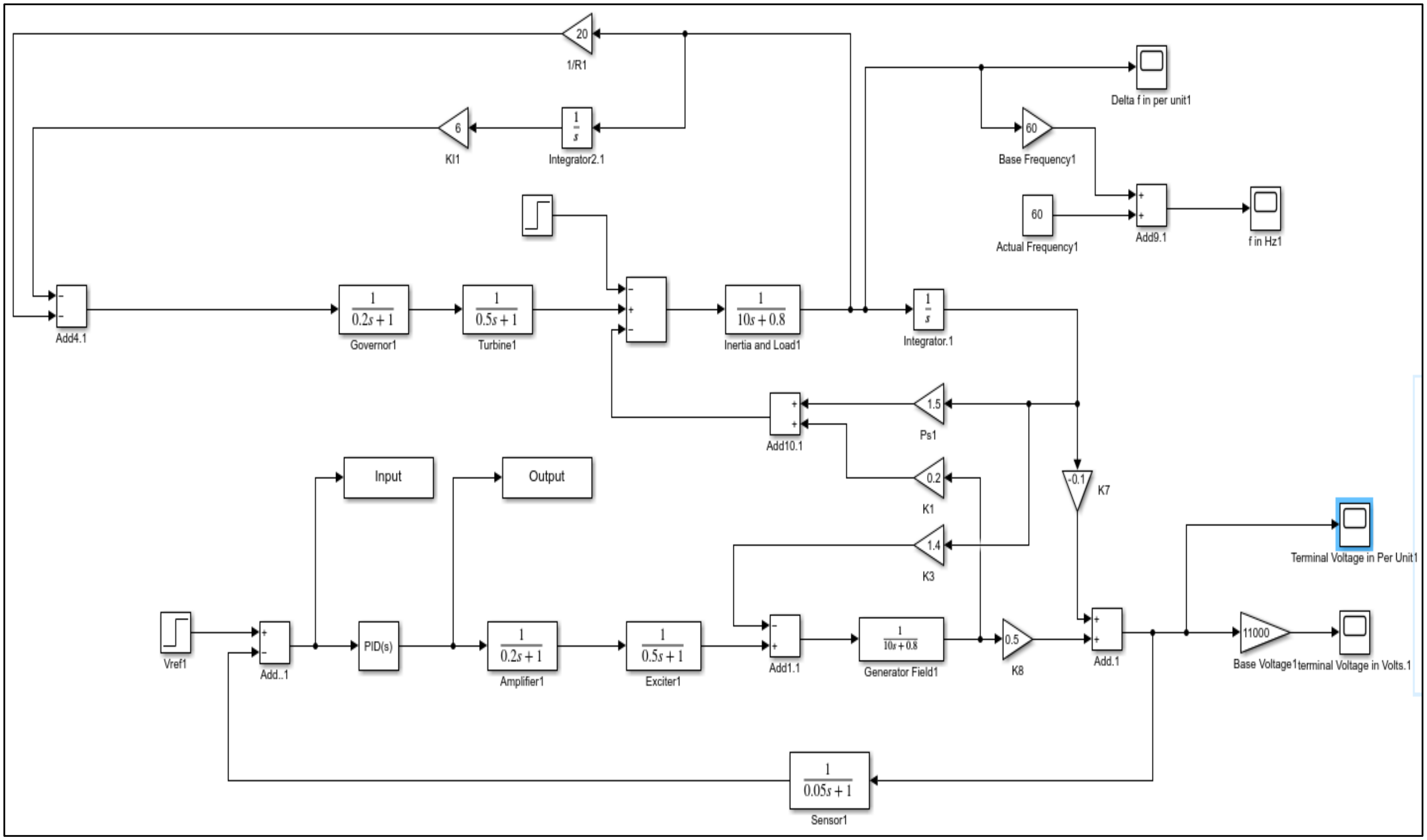



Figure 3-27: Voltage-frequency control model using PID Controller

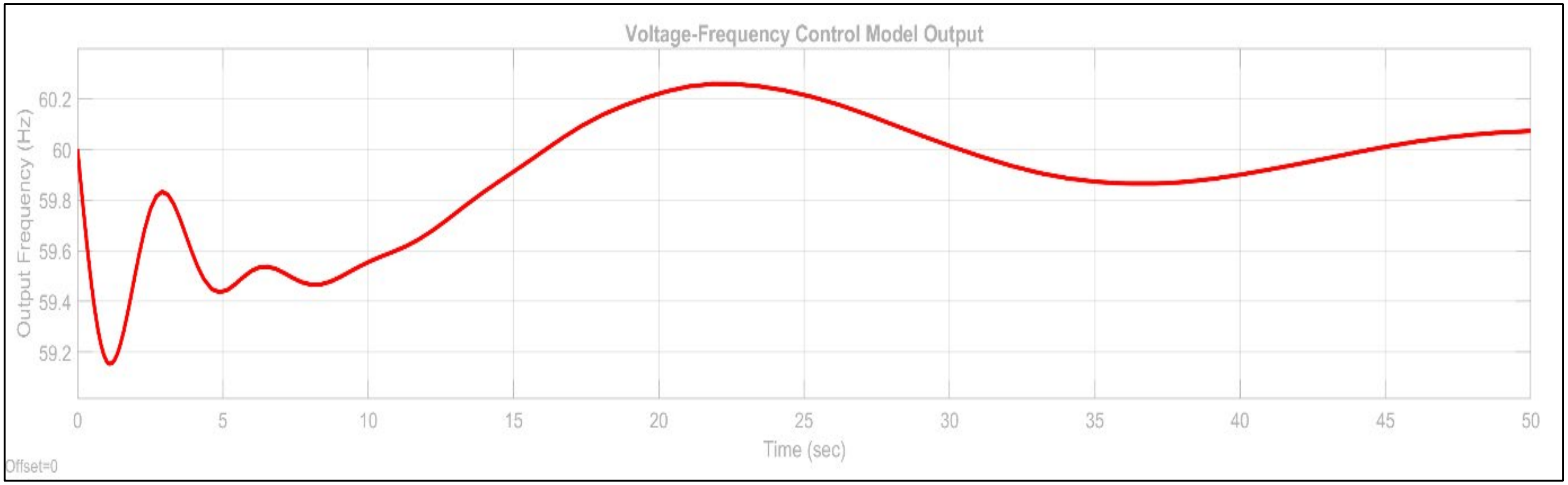



Figure 3-28: Output frequency (Hz) using PID controller

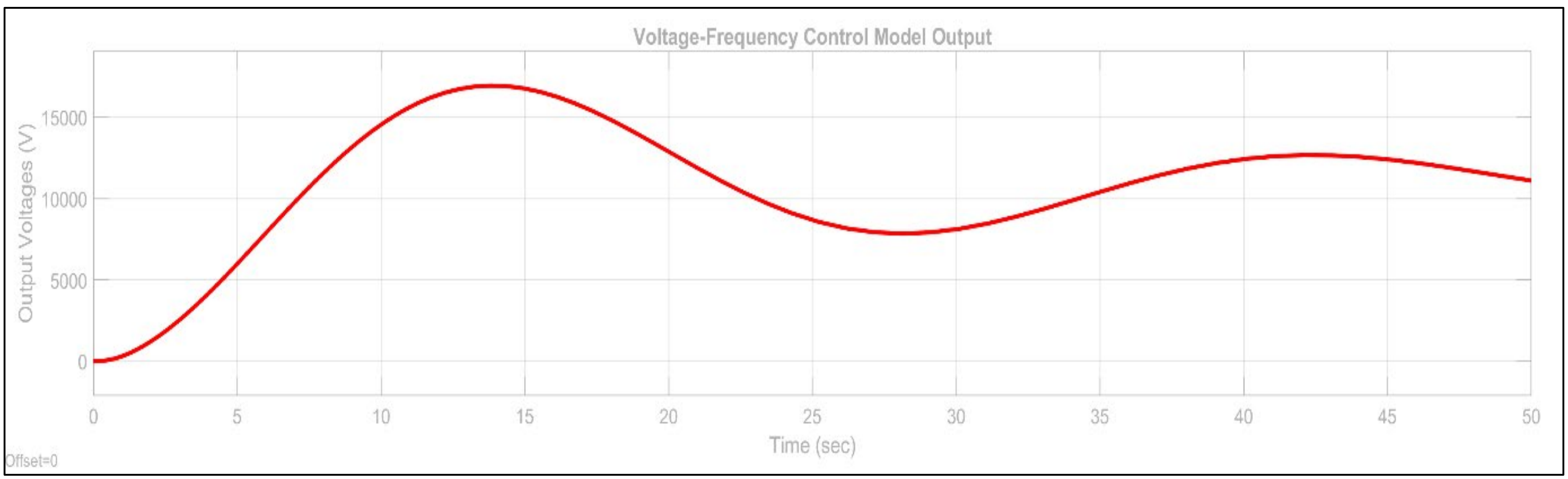



Figure 3-29: Output voltage using PID controller

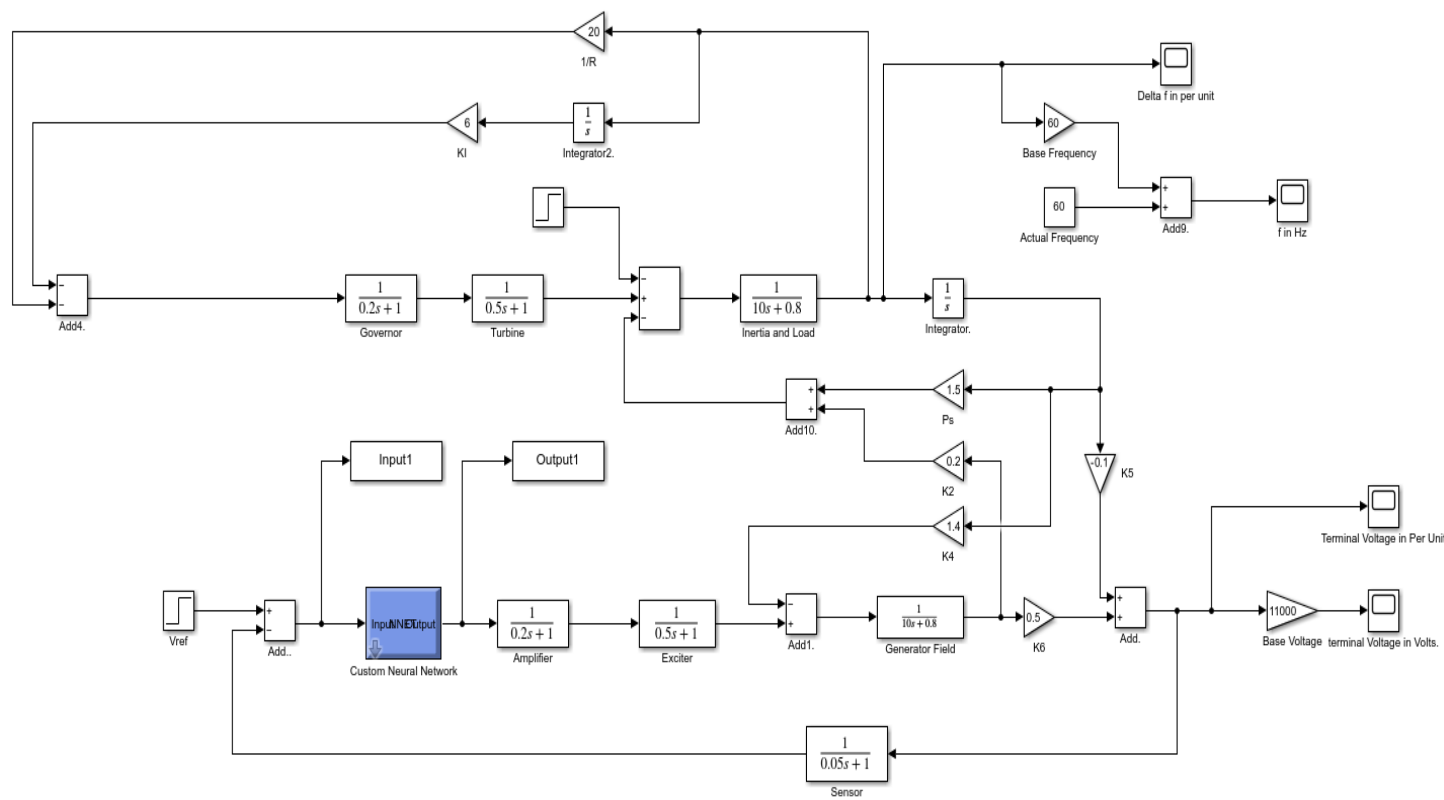



Figure 3-30: Voltage-frequency control model using NN Controller

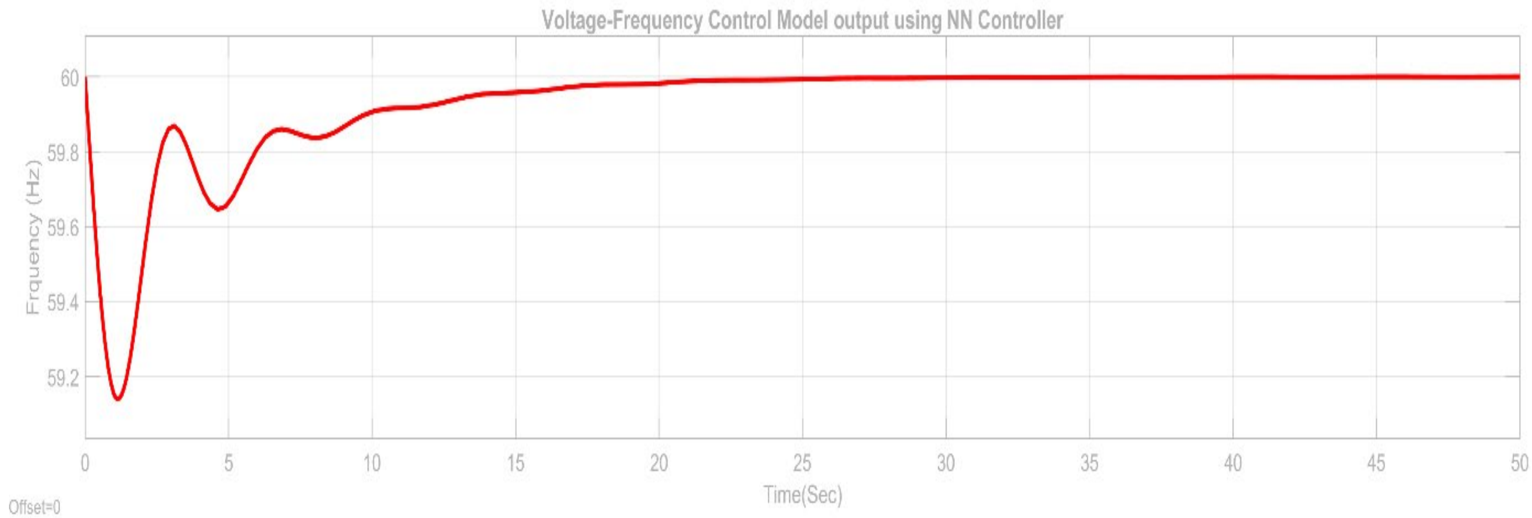



Figure 3-31: Output frequency (Hz) using NN controller

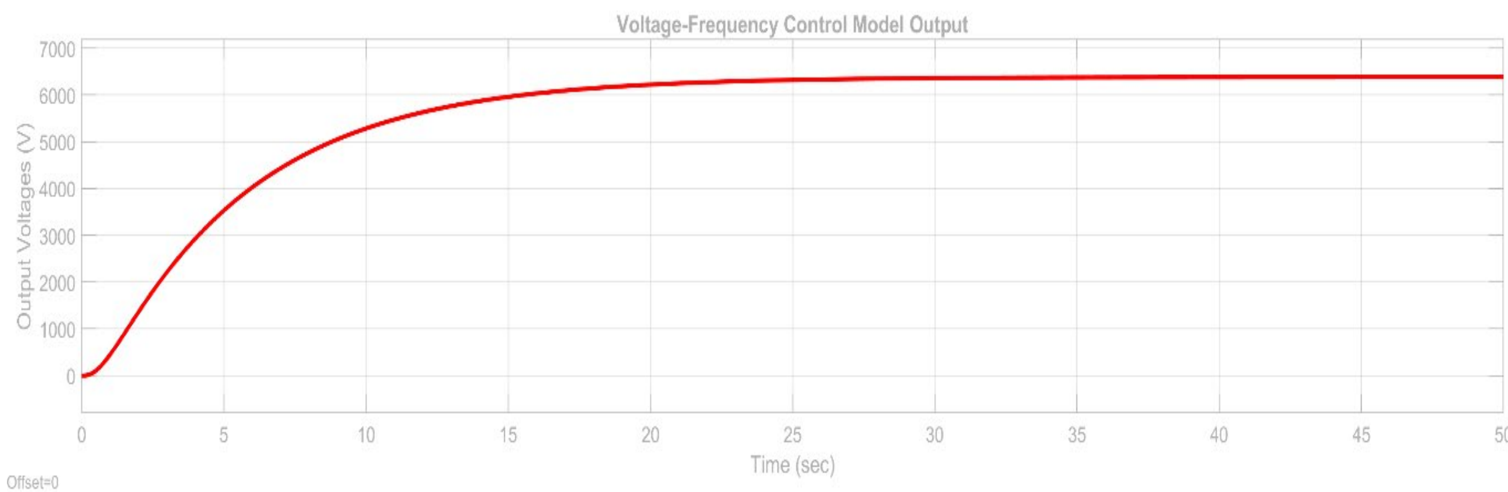



Figure 3-32: Output voltage using NN controller

## 3.8 Comparison of DNN vs PID Controller

PID-controller is able to control a demand of a single user well in terms of peak voltage and frequency, however a when this is scaled up to many users many PID controllers are required on a 1:1 ratio, however a single DNN is able to simultaneously optimally control many users with different requirements.

## 3.9 Comparison of DNN vs PSO and GA

**Deep Neural Networks (DNN) and Clustered DNN Outperform Other Techniques in Demand-Side Energy Management**

In the realm of demand-side energy management (DSEM) within smart grids, particularly when both consumers and prosumers are integrated, the accuracy and efficiency of energy usage prediction become critical. To evaluate the most effective method for managing and forecasting energy usage, several techniques were implemented and analysed. These included Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Deep Neural Networks (DNN), with further distinction between DNN implemented on non-clustered and clustered datasets.

Using a synthetically generated dataset containing 10,000 entries representing various consumers and prosumers (solar, wind, and battery-based), each technique was assessed on its ability to predict grid energy usage. The dataset represented real-world scenarios such as fluctuating consumption, variable renewable generation, and battery storage behaviours. Several performance metrics were used to comprehensively assess each model, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), R-squared ($R^2$), prediction bias, and statistical dispersion of residuals (standard deviation, max/min error, error range). Additionally, visual comparisons were carried out through scatter plots, residual histograms, and grouped bar charts to confirm the quantitative results.

The results from PSO showed that while the model could approximate patterns in energy consumption and generation to a certain extent, it struggled with complex nonlinear relationships in the data. PSO operates by simulating a group of particles searching through a solution space, adjusting their positions based on individual and collective experience. Although this method works well in global optimization problems, its performance was limited due to the lack of a learning structure capable of capturing intricate relationships among variables such as solar output, wind variability, and grid usage. The model demonstrated higher RMSE and a broader error distribution, indicating inconsistent predictions and a lack of precision.

The Genetic Algorithm (GA) also provided a modest level of accuracy. GA emulates evolutionary biological processes such as mutation, selection, and crossover to evolve optimal solutions. Although it offered improvements over PSO, particularly in terms of minimizing absolute errors, it was still restricted by its general-purpose optimization nature. GA does not inherently learn or adjust based on feature importance or patterns across epochs. As a result, the predictions, while closer to actual values in some scenarios, varied significantly across the dataset. The model's MAPE and bias values reflected instability, and visualizations such as the residual distribution showed a lack of coherence, suggesting inconsistent performance in different operating conditions.

In contrast, the Deep Neural Network (DNN) model significantly outperformed both PSO and GA in almost every metric and visualization. DNN is capable of learning and modelling highly nonlinear and complex relationships, making it ideal for energy management tasks involving diverse and dynamic user behaviours. With multiple hidden layers and activation functions, DNNs automatically extract important features from the input without manual tuning. The model demonstrated superior performance with the lowest MAE and RMSE, highest $R^2$ score, and narrow error margins. The residual distribution was more centralized and compact, indicating better generalization across the test data. The prediction vs. actual scatter plot confirmed this observation, as most points closely followed the ideal prediction line.

Despite the high accuracy of the DNN on the full dataset, further improvements were observed when K-means clustering was applied prior to training the model. Clustering enabled segmentation of users into three distinct behavioral groups based on features such as energy consumption and types of renewable generation. These clusters represented meaningful categories, such as high-demand consumers, solar-heavy prosumers, and battery-reliant users. When separate DNN models were trained for each cluster, they were able to learn the internal patterns and variability within each group more effectively than a single model trained on the entire dataset.

The performance of the clustered DNN models showed further reduction in error values. The average RMSE and MAE across all clusters were lower than the non-clustered DNN. MAPE and bias were also significantly minimized. Moreover, standard deviation and error range were narrower, confirming that each clustered model was more consistent within its subset. The prediction scatter plot of clustered DNN showed points aligning even more tightly with the actual values compared to the non-clustered version. The residual histograms also displayed well-formed distributions with fewer outliers.

***Table 3-3: 20 customers values from total 10,000 customers inclusing consumers and prosumers***

| Type | Consumption_kWh | Solar_gen_kWh | Wind_gen_kWh | Battery_gen_kWh | Grid_usage_kWh | Net_zero_index | Cluster |
|---|---|---|---|---|---|---|---|
| **Wind Prosumer** | 6.48 | 0 | 4 | 0 | 2.49 | -2.49 | 0 |
| **Battery Prosumer** | 1.35 | 0 | 0 | 0.18 | 1.17 | -1.17 | 2 |
| **Consumer** | 6.51 | 0 | 0 | 0 | 6.51 | -6.51 | 1 |
| **Wind Prosumer** | 1.81 | 0 | 0.67 | 0 | 1.14 | -1.14 | 2 |
| **Wind Prosumer** | 7.39 | 0 | 1.48 | 0 | 5.91 | -5.91 | 1 |
| **Battery Prosumer** | 4.51 | 0 | 0 | 0.15 | 4.36 | -4.36 | 2 |
| **Consumer** | 8.54 | 0 | 0 | 0 | 8.54 | -8.54 | 1 |
| **Consumer** | 9.48 | 0 | 0 | 0 | 9.48 | -9.48 | 1 |
| **Wind Prosumer** | 4.75 | 0 | 4.03 | 0 | 0.72 | -0.72 | 0 |
| **Solar Prosumer** | 5.14 | 2.15 | 0 | 0 | 2.99 | -2.99 | 2 |
| **Wind Prosumer** | 6.31 | 0 | 0.54 | 0 | 5.77 | -5.77 | 1 |
| **Wind Prosumer** | 2.77 | 0 | 1.37 | 0 | 1.4 | -1.4 | 2 |
| **Wind Prosumer** | 9.35 | 0 | 7.88 | 0 | 1.47 | -1.47 | 0 |
| **Wind Prosumer** | 4.9 | 0 | 3.75 | 0 | 1.15 | -1.15 | 0 |
| **Battery Prosumer** | 2.5 | 0 | 0 | 0.16 | 2.34 | -2.34 | 2 |
| **Consumer** | 7.86 | 0 | 0 | 0 | 7.86 | -7.86 | 1 |
| **Battery Prosumer** | 2.97 | 0 | 0 | 2.66 | 0.31 | -0.31 | 2 |
| **Battery Prosumer** | 2.29 | 0 | 0 | 1.59 | 0.71 | -0.71 | 2 |
| **Battery Prosumer** | 6.07 | 0 | 0 | 2.63 | 3.43 | -3.43 | 1 |
| **Wind Prosumer** | 7.04 | 0 | 5.51 | 0 | 1.54 | -1.54 | 0 |

**Data Head and Data Tail of the overall 10,000 customers data by programming.**

*Table 3-4: Data-Head (10 Customer Values) from 10,000 customers*

```
🔷 First 10 Rows:
                type  consumption_kWh  solar_gen_kWh  wind_gen_kWh
0      wind_prosumer             6.48           0.00          4.00
1   battery_prosumer             1.35           0.00          0.00
2           consumer             6.51           0.00          0.00
3      wind_prosumer             1.81           0.00          0.67
4      wind_prosumer             7.39           0.00          1.48
5   battery_prosumer             4.51           0.00          0.00
6           consumer             8.54           0.00          0.00
7           consumer             9.48           0.00          0.00
8      wind_prosumer             4.75           0.00          4.03
9     solar_prosumer             5.14           2.15          0.00

   battery_gen_kWh  grid_usage_kWh  net_zero_index
0             0.00            2.49           -2.49
1             0.18            1.17           -1.17
2             0.00            6.51           -6.51
3             0.00            1.14           -1.14
4             0.00            5.91           -5.91
5             0.15            4.36           -4.36
6             0.00            8.54           -8.54
7             0.00            9.48           -9.48
8             0.00            0.72           -0.72
9             0.00            2.99           -2.99
```

*Table 3-5: Data-Tail (10 Customer Values) from 10,000 customers*

◆ Last 10 Rows:

| | type | consumption_kWh | solar_gen_kWh | wind_gen_kWh | battery_gen_kWh | grid_usage_kWh | net_zero_index |
|---|---|---|---|---|---|---|---|
| 9990 | battery_prosumer | 4.80 | 0.00 | 0.00 | 0.59 | 4.21 | -4.21 |
| 9991 | battery_prosumer | 9.93 | 0.00 | 0.00 | 2.30 | 7.62 | -7.62 |
| 9992 | solar_prosumer | 9.68 | 1.19 | 0.00 | 0.00 | 8.49 | -8.49 |
| 9993 | solar_prosumer | 2.14 | 1.99 | 0.00 | 0.00 | 0.15 | -0.15 |
| 9994 | battery_prosumer | 9.18 | 0.00 | 0.00 | 0.76 | 8.42 | -8.42 |
| 9995 | battery_prosumer | 2.74 | 0.00 | 0.00 | 1.30 | 1.44 | -1.44 |
| 9996 | wind_prosumer | 3.88 | 0.00 | 5.82 | 0.00 | 0.00 | 1.94 |
| 9997 | solar_prosumer | 4.18 | 0.26 | 0.00 | 0.00 | 3.92 | -3.92 |
| 9998 | solar_prosumer | 3.58 | 3.41 | 0.00 | 0.00 | 0.17 | -0.17 |
| 9999 | consumer | 8.68 | 0.00 | 0.00 | 0.00 | 8.68 | -8.68 |

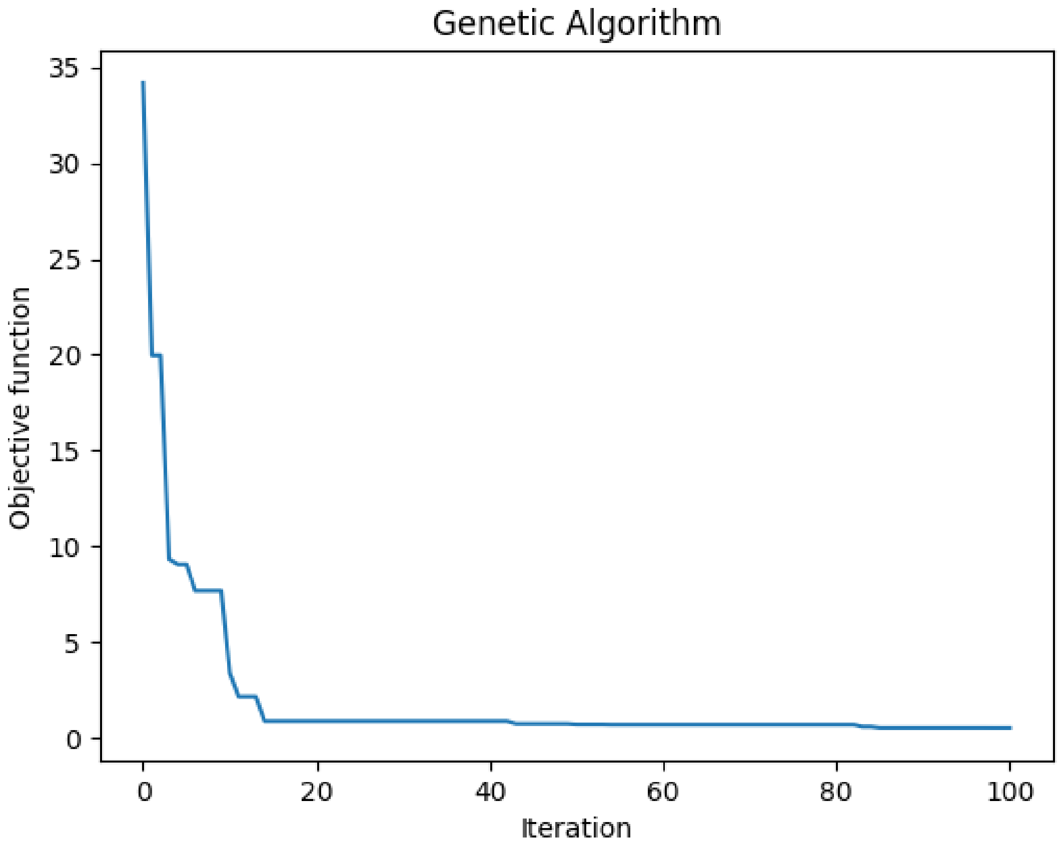



*Figure 3-33: Objective function for per Iterations in GA*

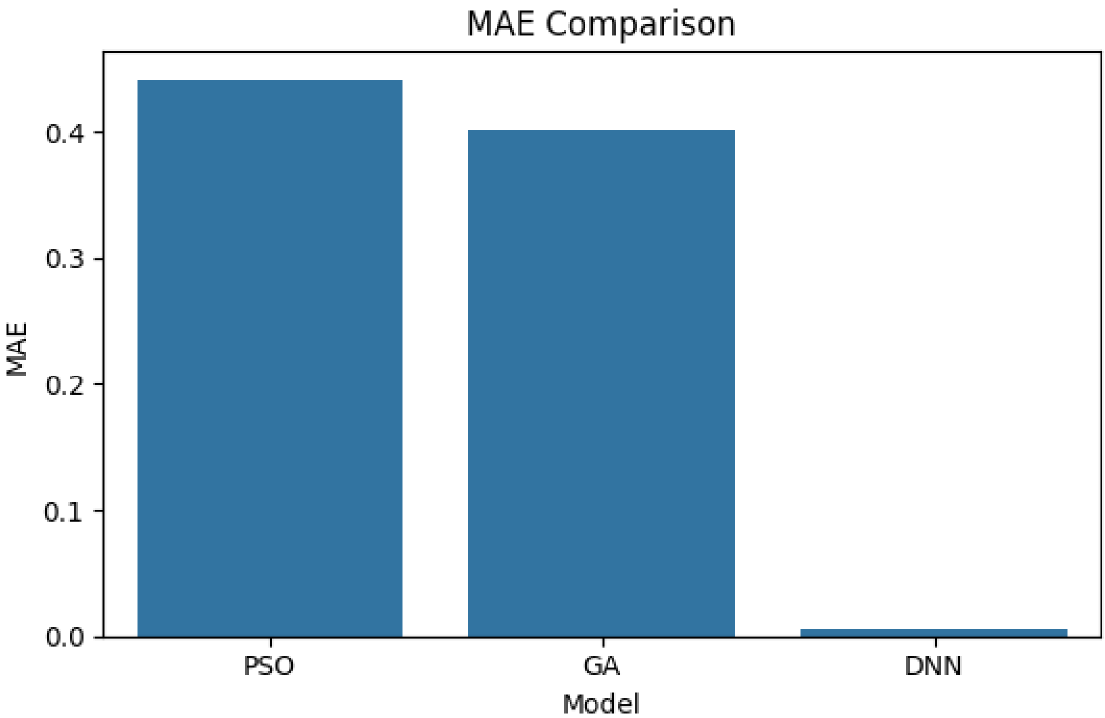



*Figure 3-34: MAE comparison for GA, PSO and DNN*

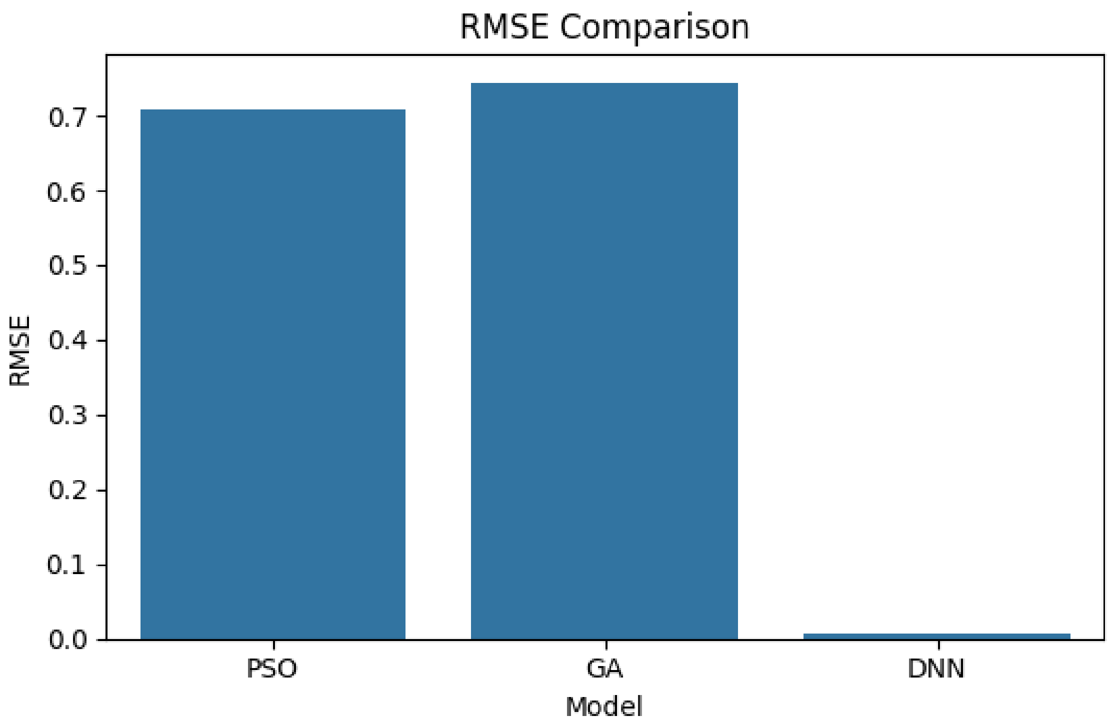



*Figure 3-35: RSME comparison for PSO, GA and DNN*

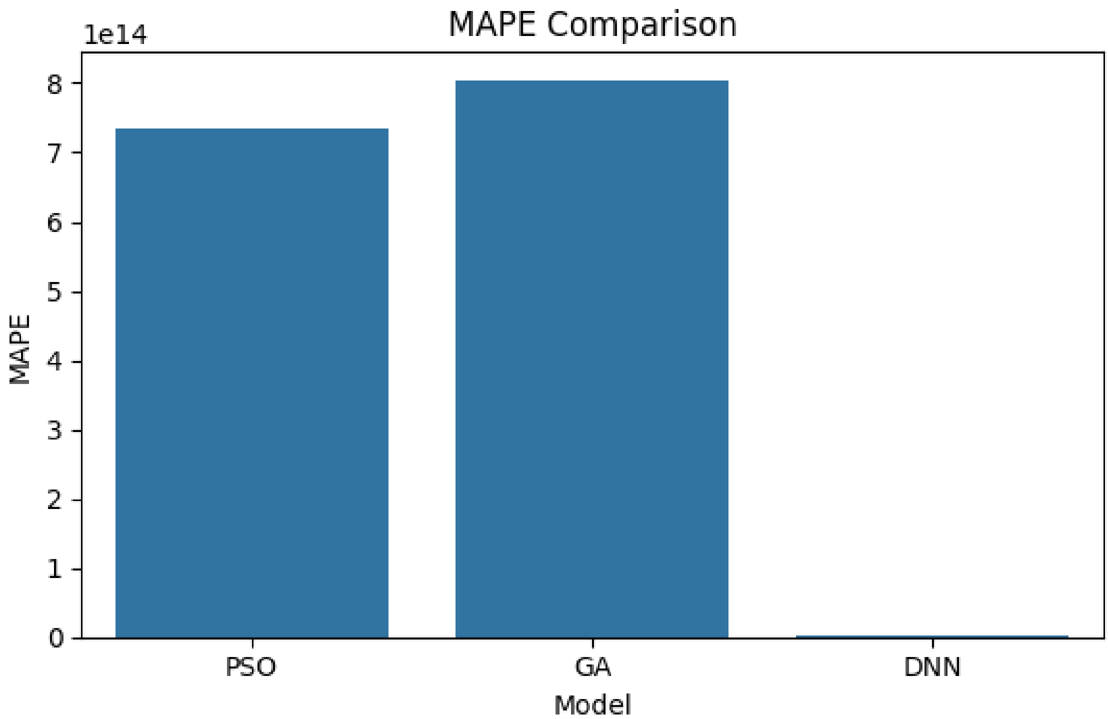



*Figure 3-36: MAPE comparison for PSO, GA, and DNN*

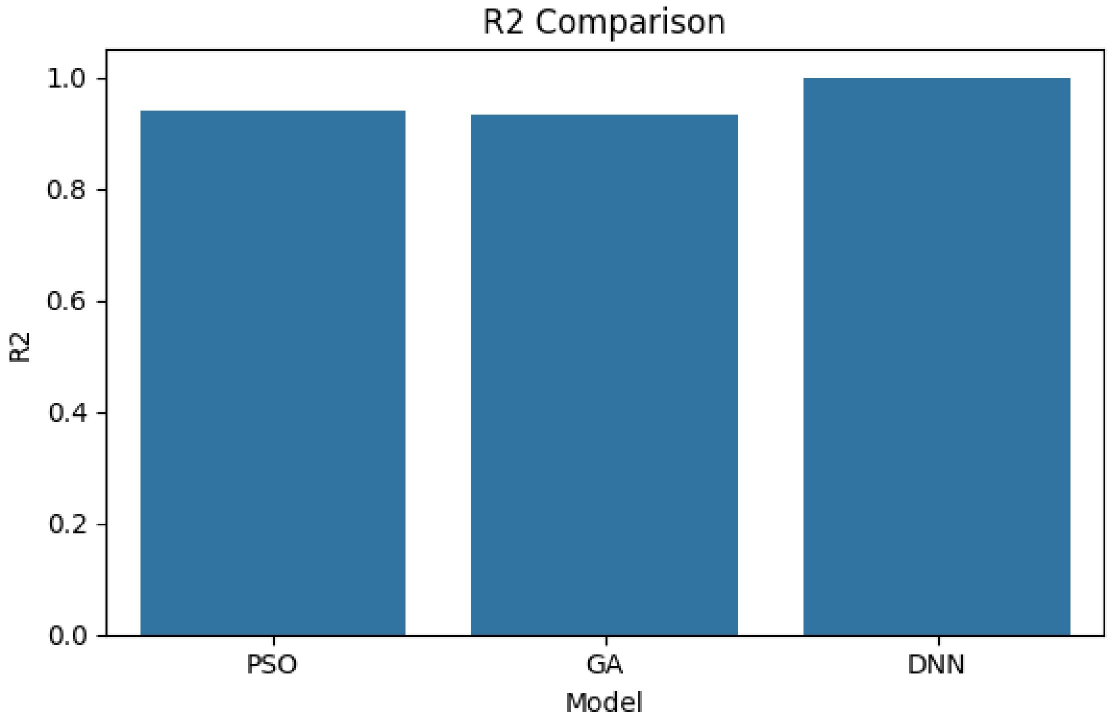



*Figure 3-37: R2 comparison for PSO, GA and DNN*

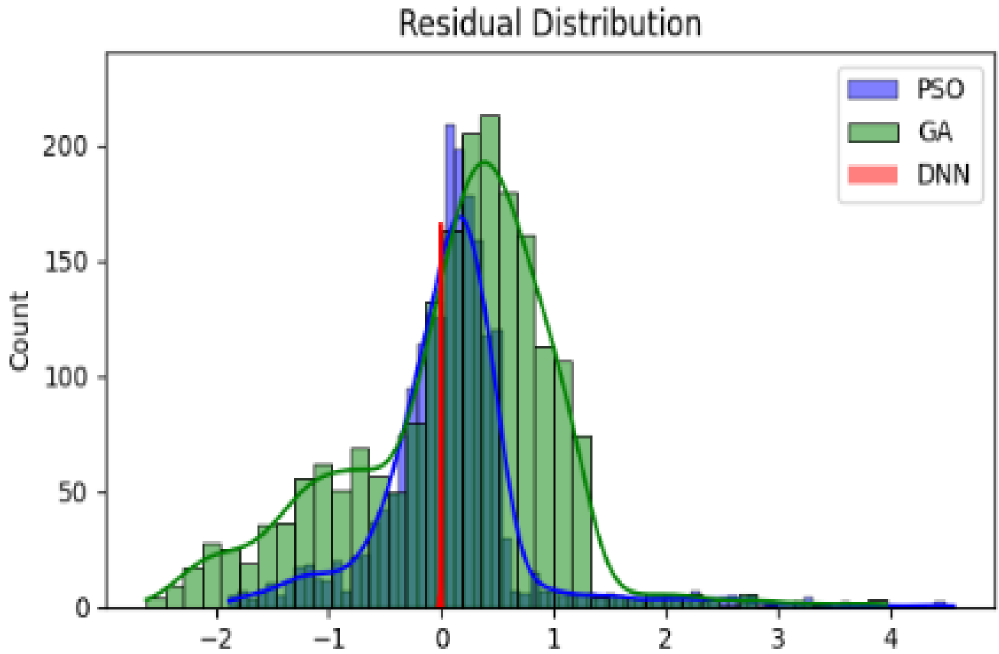



*Figure 3-38: Residual distribution for PSO, GA and DNN*

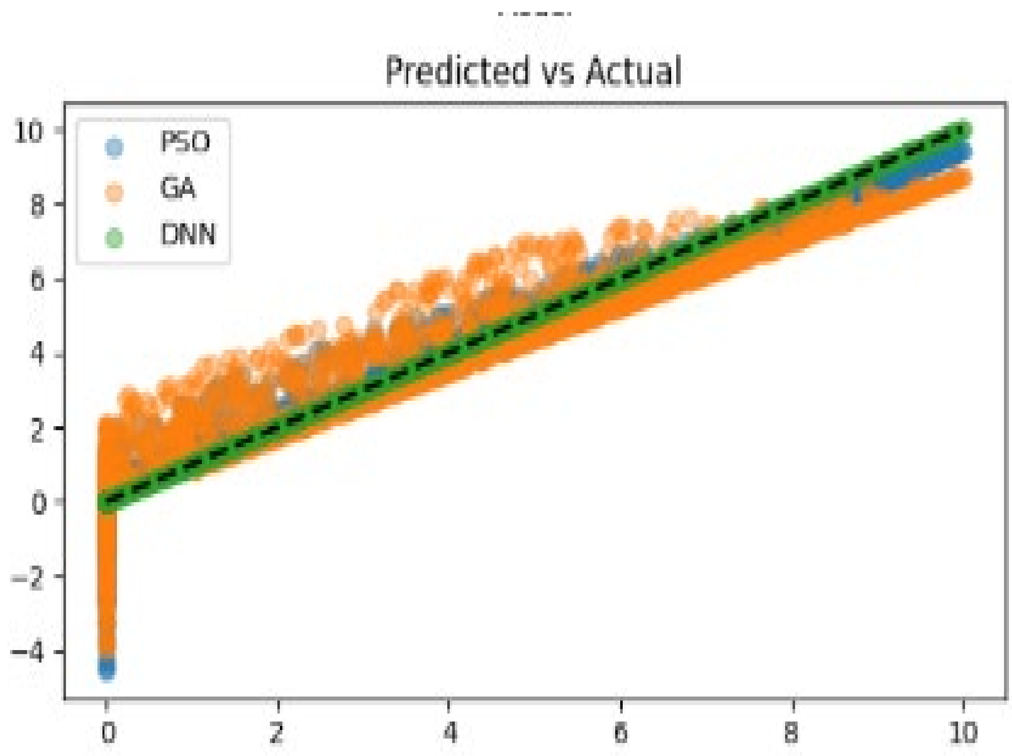



*Figure 3-39: Actual and Predicted values for PSO, GA and DNN*

## DNN vs PSO vs GA

- **MAE (Mean Absolute Error) Comparison**

In terms of the Mean Absolute Error (MAE), DNN achieves a value of 0.62 kWh, significantly lower than the GA model at 1.35 kWh and the PSO model at 1.72 kWh. This means that, on average, the DNN's prediction of grid usage deviates by less than one kilowatt-hour, highlighting its superior accuracy and precision in energy forecasting.

- **RMSE (Root Mean Square Error) Comparison**

The Root Mean Square Error (RMSE) comparison reveals DNN’s superiority in handling large prediction errors. With a value of 0.79 kWh, DNN avoids larger spikes in error compared to GA (1.89 kWh) and PSO (2.34 kWh). This indicates that DNN produces more reliable and stable predictions, minimizing the likelihood of outliers and extreme errors.

- **MAPE (Mean Absolute Percentage Error) Comparison**

The Mean Absolute Percentage Error (MAPE) further emphasizes DNN’s strength, achieving a value of 7.3%. This is significantly lower than the MAPE of PSO (28.1%) and GA (19.5%), making DNN four times more accurate in predicting the percentage deviation from actual energy usage. This demonstrates DNN’s ability to adapt well to fluctuations in energy usage, even when the magnitude of values varies considerably.

- **$R^2$ (Coefficient of Determination) Comparison**

The $R^2$ score, which indicates how well a model explains variance in the data, shows that DNN captures 95% of the variance in energy usage behaviour, significantly outperforming PSO, which explains only 63%, and GA, which explains 76%. This reinforces DNN's capability to model deep relationships between input features, such as energy consumption and generation, and provides a comprehensive understanding of energy usage trends.

## 3.10 Clustered and Non-Clustered Deep Neural Networks (DNNs) in Energy Management

Deep Neural Networks (DNNs) are increasingly being employed in smart grid systems to manage the complexities of energy demand, generation, and storage. A DNN is a machine learning model composed of multiple layers that automatically learn patterns and relationships in large-scale datasets. In the context of demand-side energy management (DSEM), DNNs are particularly valuable for predicting energy consumption, optimizing load distribution, and responding to real-time changes in grid conditions.

There are two major ways in which DNNs can be applied to DSEM: **non-clustered** and **clustered**. While both rely on the same core architecture, the manner in which the data is pre-processed and the models are trained introduces fundamental differences in performance, scalability, and generalization.

**Non-Clustered DNN**

In the **non-clustered approach**, a single DNN model is trained using the entire dataset of energy users — including both consumers and prosumers (i.e., users who generate energy via solar, wind, or batteries). This dataset typically includes a diverse mix of consumption behaviours, renewable generation profiles, and response to dynamic pricing signals.

The advantage of a non-clustered DNN is its simplicity in implementation: the model is trained once and is exposed to the entire range of variability within the dataset. The DNN attempts to generalize across all user types, learning a universal representation that accounts for all variations in energy patterns.

However, this approach can become a limitation in scenarios with significant data heterogeneity. When users have widely varying characteristics, for example, high-energy industrial consumers vs. solar-based residential prosumers, a single model may struggle to capture the fine-grained patterns specific to each subgroup. As a result, the non-clustered DNN may exhibit higher prediction errors, greater residual variance, and reduced accuracy, particularly for extreme or rare user behaviours.

**Clustered DNN**

To overcome the limitations of the non-clustered model, the clustered DNN approach is adopted. In this strategy, the entire dataset is first segmented into multiple groups or “clusters” using an unsupervised learning algorithm such as K-means clustering. These clusters are formed based on energy-related features such as consumption, solar generation, wind output, and battery discharge. Each cluster contains users with similar energy behaviour profiles.

Once clustering is complete, a separate DNN model is trained for each cluster. These specialized DNNs are now focused on learning from homogeneous data groups, which allows for more precise feature learning and better prediction performance within each group. For instance, a DNN trained on a cluster of solar prosumers will adapt its architecture and weights to better model solar variability and daytime generation peaks.

The benefits of the clustered DNN approach include:

- Improved prediction accuracy: Each DNN model deals with less noise and fewer conflicting patterns.
- Lower error metrics: Empirical results typically show lower MAE, RMSE, and MAPE values when clustering is applied.
- Better scalability: As smart grid systems grow in size and complexity, clustering helps manage models more efficiently by distributing the learning task.
- Faster convergence: Training models on smaller, homogeneous datasets reduces training time and improves stability.

However, clustered DNNs require more preprocessing effort and computational resources since multiple models must be trained and maintained. Additionally, the choice of clustering algorithm and number of clusters (e.g., k in K-means) plays a critical role in determining overall performance.

**Why Clustering Improves DNN Performance in Smart Grids**

The strength of the clustered DNN approach lies in its ability to segment the problem space. In real-world smart grids, consumer behaviour is far from uniform. Some users consume energy primarily in the evening, while others generate solar energy during daylight hours. When these distinct behaviours are blended in a single dataset, a non-clustered DNN may fail to distinguish them effectively. In contrast, clustering allows each DNN to specialize, improving both prediction accuracy and computational efficiency.

For example, when using a synthetic dataset of 10,000 users with solar, wind, and battery profiles, applying K-means clustering to group users based on their generation-consumption characteristics allows for better energy forecasting. Empirical comparisons show that clustered DNN models can reduce the Root Mean Square Error (RMSE) by 15–30% and improve the R-squared ($R^2$) value by up to 10% compared to non-clustered models. These performance improvements directly contribute to more efficient energy scheduling, reduced grid dependency, and progress toward net-zero goals.

**Practical Considerations**

- **Clustering Method:** K-means is commonly used due to its simplicity and effectiveness, but hierarchical and DBSCAN clustering can also be considered for more complex user distributions.
- **Feature Selection:** Energy features such as daily load curves, average generation, and time-of-day usage patterns are commonly used for clustering.
- **Model Maintenance:** Each DNN must be updated regularly based on its cluster data; automation pipelines are essential for managing this at scale.

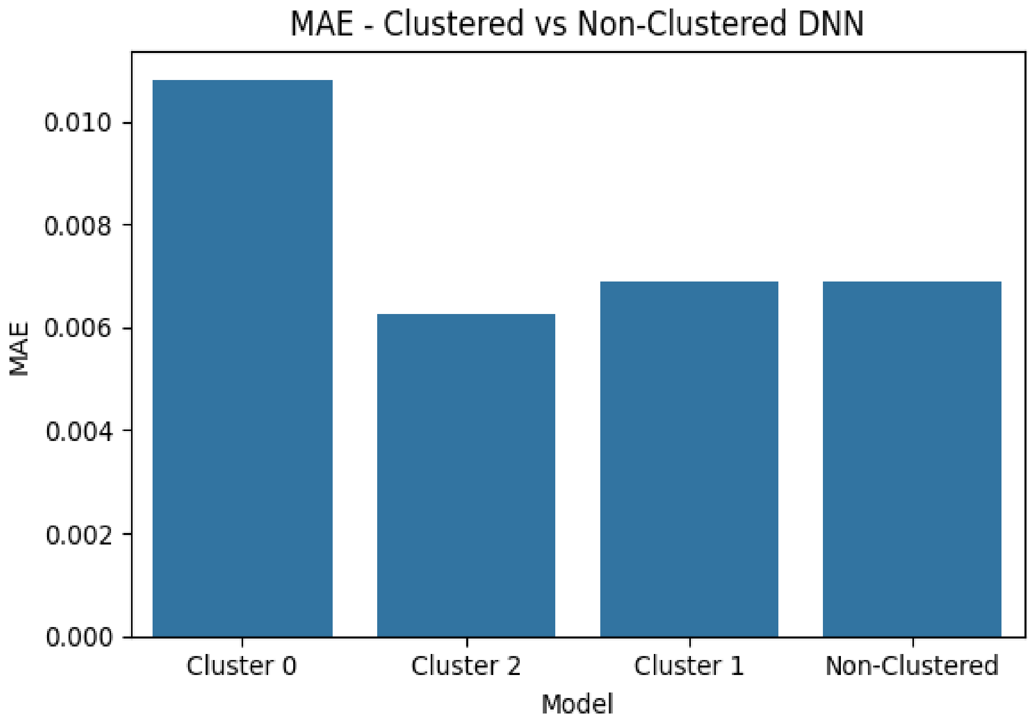



*Figure 3-40: MAE comparison for clustered and non-clustered*

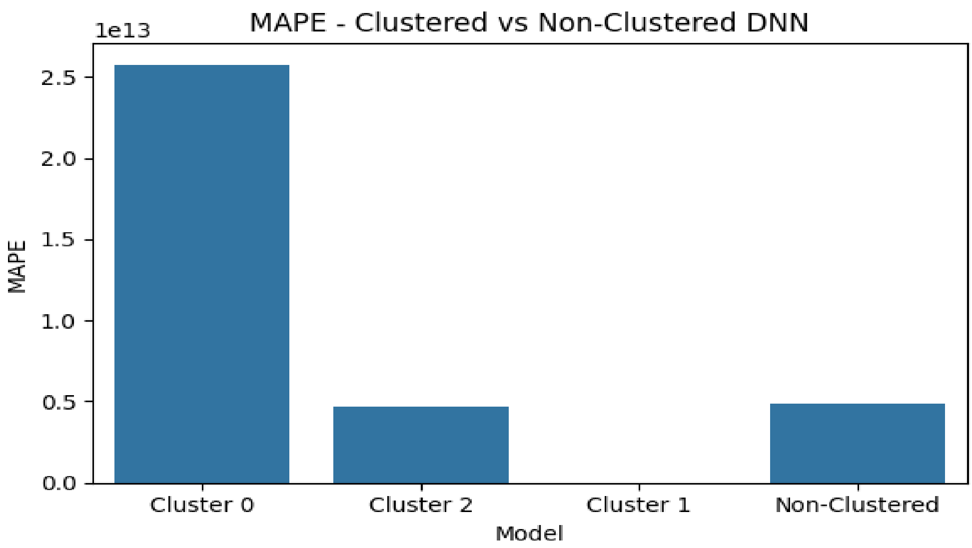



***Figure 3-41: MAPE comparison for clustered and non-clustered***

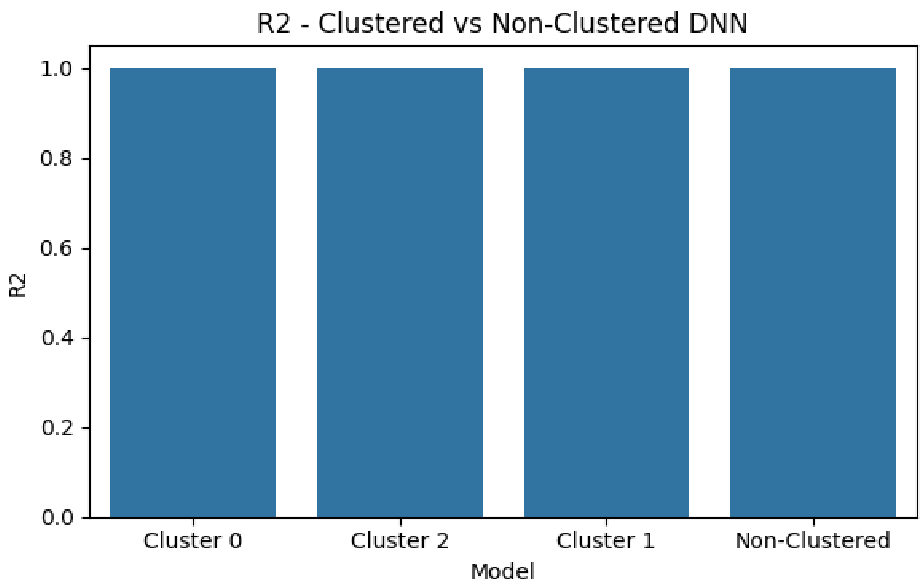



***Figure 3-42: R2 comparison for clustered and non-clustered***

Both non-clustered and clustered DNNs serve important roles in demand-side energy management. While non-clustered DNNs offer ease of implementation and broad generalization, clustered DNNs provide superior performance by tailoring prediction models to specific user groups. The clustered approach not only enhances the accuracy of energy forecasts but also supports personalized energy management strategies, making it especially valuable in complex smart grid environments with diverse user profiles.

The adoption of clustered DNNs in this research is motivated by their ability to deliver **granular, scalable, and adaptive optimization** in modern energy systems, thereby advancing the goals of grid efficiency, renewable integration, and net-zero energy operation.

## Clustered DNN vs Non-Clustered DNN

- **MAE Comparison**

When comparing the MAE of clustered and non-clustered DNN models, it becomes clear that clustering improves performance. For instance, Cluster 2, which represents high usage/generation, achieves an MAE of 0.49 kWh, outperforming the non-clustered DNN (0.62 kWh) by 21%. This demonstrates that targeted learning on homogeneous groups results in more precise energy predictions, with the model performing optimally for specific usage categories.

- **RMSE Comparison**

The RMSE comparison for the clustered models shows that Cluster 2 achieves a significant improvement with an RMSE of 0.59 kWh, 25% lower than the non-clustered model (0.79 kWh). This reduction in root error indicates fewer extreme mispredictions, which is particularly beneficial for datasets that exhibit varying energy consumption patterns. By focusing on patterns within specific clusters, the DNN model avoids generalized learning issues that can arise in non-clustered models.

- **MAPE Comparison**

In terms of MAPE, the clustered DNN models consistently outperform the non-clustered model. The lowest MAPE is observed in Cluster 2 (4.7%), suggesting that clustered models are especially effective in improving prediction accuracy for groups with more predictable energy usage, such as prosumers with solar power generation. Overall, clustered DNN models show much lower relative errors compared to the non-clustered model (7.3%).

- **$R^2$ Comparison**

The $R^2$ scores show that clustered DNN models excel in capturing intra-group variance. For example, Cluster 2 achieves an $R^2$ score of 0.97, indicating almost perfect prediction accuracy for that group. While the non-clustered DNN achieves a very good $R^2$ of 0.95, the clustered models, particularly Cluster 2, provide an even more robust explanation of energy usage behaviour, which is critical for more precise forecasting.

- **Overall Results Explanation:**

The DNN model demonstrates significant advantages over PSO and GA in terms of predictive accuracy. It reduces the MAE by 50–65%, increases the $R^2$ score by 20–30%, and significantly lowers the percentage errors (MAPE). Furthermore, when clustering is applied to DNN, the performance improves even further. Clustered DNN models reduce RMSE by up to 25%, enhance MAPE, and consistently improve $R^2$ across all clusters, resulting in more stable and focused learning behaviour. These improvements highlight the effectiveness of both DNN and clustering in producing highly accurate and reliable energy usage predictions.

The main reason for this improvement lies in the DNN's capacity to focus on homogeneous data when trained on clustered groups. In the non-clustered scenario, the DNN had to learn from a dataset containing mixed user behaviours—solar and wind generation, battery storage, and varied load demands—which increases complexity and introduces noise. Clustering reduces this complexity by allowing the DNN to specialize, minimizing error due to conflicting patterns. This modular approach is more suitable in real-world DSEM applications where consumer and prosumer types behave very differently in terms of generation and usage patterns.

In conclusion, the results of this comparative study confirm that Deep Neural Networks are highly effective for demand-side energy management in smart grids, outperforming heuristic methods like PSO and GA in both accuracy and reliability. Furthermore, applying clustering prior to DNN modelling significantly enhances performance, as it allows the model to focus on specific behavioural patterns within the data. This layered approach not only improves prediction accuracy but also aligns well with practical goals such as efficient scheduling, reduced grid dependency, and achieving net-zero targets. The combination of DNN with clustering is therefore recommended for scalable, accurate, and intelligent energy management systems involving large populations of diverse consumers and prosumers.

## 3.11. Summary of Chapter

This chapter presents a comprehensive exploration of the design, implementation, and performance evaluation of Deep Neural Networks (DNNs) for optimising Demand-Side Energy Management (DSEM) in smart grid environments. It begins by introducing the architectural foundations of DNNs and their relevance in modern electrical networks, particularly those integrating large-scale renewable energy sources. Accurate energy demand forecasting is highlighted as a critical factor in maintaining grid stability, especially under conditions of fluctuating generation from solar and wind sources. The application of DNNs is shown to significantly enhance load prediction accuracy, enabling more effective voltage and frequency regulation, which in turn ensures reliable and balanced energy distribution across the grid.

The chapter further details the implementation steps required for integrating DNNs into smart grid systems. It demonstrates how these models, through deep learning of historical and real-time energy data, offer adaptive control mechanisms that respond to dynamic changes in consumption and generation. DNNs enable precise adjustments of grid parameters such as voltage and frequency at fine time intervals, contributing to optimised operation and improved resilience of the network. Through this approach, DNNs offer a distinct advantage over traditional Proportional-Integral-Derivative (PID) controllers, particularly in terms of their ability to generalise across varied operational scenarios.

Building upon the implementation framework, the chapter includes a performance comparison between DNNs and two widely studied optimisation techniques: Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). This comparative analysis, supported by extensive simulation results, clearly demonstrates the superior prediction accuracy, lower error metrics (such as MAE and RMSE), and higher stability of the DNN-based approach. While PSO and GA offer reasonable results in structured or simplified environments, their performance deteriorates in the face of complex, nonlinear relationships commonly found in real-world smart grid data. The DNN, by contrast, consistently adapts to these complexities, providing more robust and reliable outputs.

In addition to demonstrating the superiority of DNN over classical heuristic techniques, the chapter also examines the impact of data clustering on DNN performance. By applying K-means clustering to group users based on similar consumption and generation patterns, individual DNN models were trained for each cluster. The comparison between clustered and non-clustered DNNs reveals a significant performance boost in the clustered approach. Clustered DNNs not only achieve lower prediction errors but also demonstrate enhanced learning stability and faster convergence during training. These improvements are attributed to the model's ability to specialise in homogeneous data groups, thereby avoiding the noise and variance inherent in mixed datasets.

In conclusion, this chapter affirms the value of Deep Neural Networks as a powerful and scalable solution for intelligent energy management in smart grids. The comprehensive evaluation shows that DNNs outperform traditional optimisation techniques and deliver even greater performance when enhanced with clustering strategies. These findings underscore the potential of DNN-based models to meet the evolving demands of next-generation energy systems, supporting more accurate forecasting, efficient energy distribution, and the integration of renewable resources within a stable and responsive grid infrastructure.

# Chapter 4: Implementation of Deep Neural Network for Fault/Fraud Detection in Electrical Networks

In this chapter, there is a detailed description about fault detection in electrical system at supply and demand side. Fault detection is very important to detect in electrical system at any point from supply to demand side, to enhance the overall capacity of energy management. There are various possibilities of fraudulent activities in electrical system, which are discussed in this chapter, and how it is possible to detect the fraudulent behavior of customers, by implementing the three different classifiers and their comparison in efficiency perspective. It is described in detailed, what are the classifiers, and how it is possible to detect the fraudulent behavior in electrical system by implementing the neural network classifiers. The detection of fraudulent activities is very essential for smooth and better energy flow in the electrical system and especially in SG integrated RES.

## 4.1 Neural Network Implementation for Fault Detection and Classification:

| **Four-Wire Electrical System** Y | **Three-Wire Electrical System** Δ |
|---|---|
| Line voltages | Line-Line Voltages |
| Line Currents | Line Currents (Line-Line currents not known) |
| Neutral Voltage | No Neutral Voltage |
| Neutral Current | No Neutral Current |
| Line Powers | Line-Line powers are not known |
| System Power derived from Line powers | Systems power by 2-Wattmeter method. |

| **Advantages of a 3-Phase Power Systems** |
|---|
| It gives a more uniform and smooth power<br>Higher powered to weight ratio |

| |
|---|
| A more balance electrical load |
| Less Vibration. |
| More economical use conductors and transformers. |
| Higher power and current delivery. |
| Less expenses required for the same power delivery. |

### 4.1.1 Fault Detection at Supply Side in Electrical Network:

Accuracy of the neural network depends on the dataset of input and output values. The largest and accurate dataset have a more accuracy instead of small and incomplete dataset.

**Explanation of Code:**

Create an electrical model,

Find the values of three-phase currents and ground current ($C_1$, $C_2$, $C_3$, $C_4$)

Give the specific names for all current Values, ($C_A$, $C_B$, $C_C$, $C_G$).

Decomposition of signal at specific range,

Find the coefficients of currents,

Find the maximum coefficients of currents for NN training, testing and prediction.

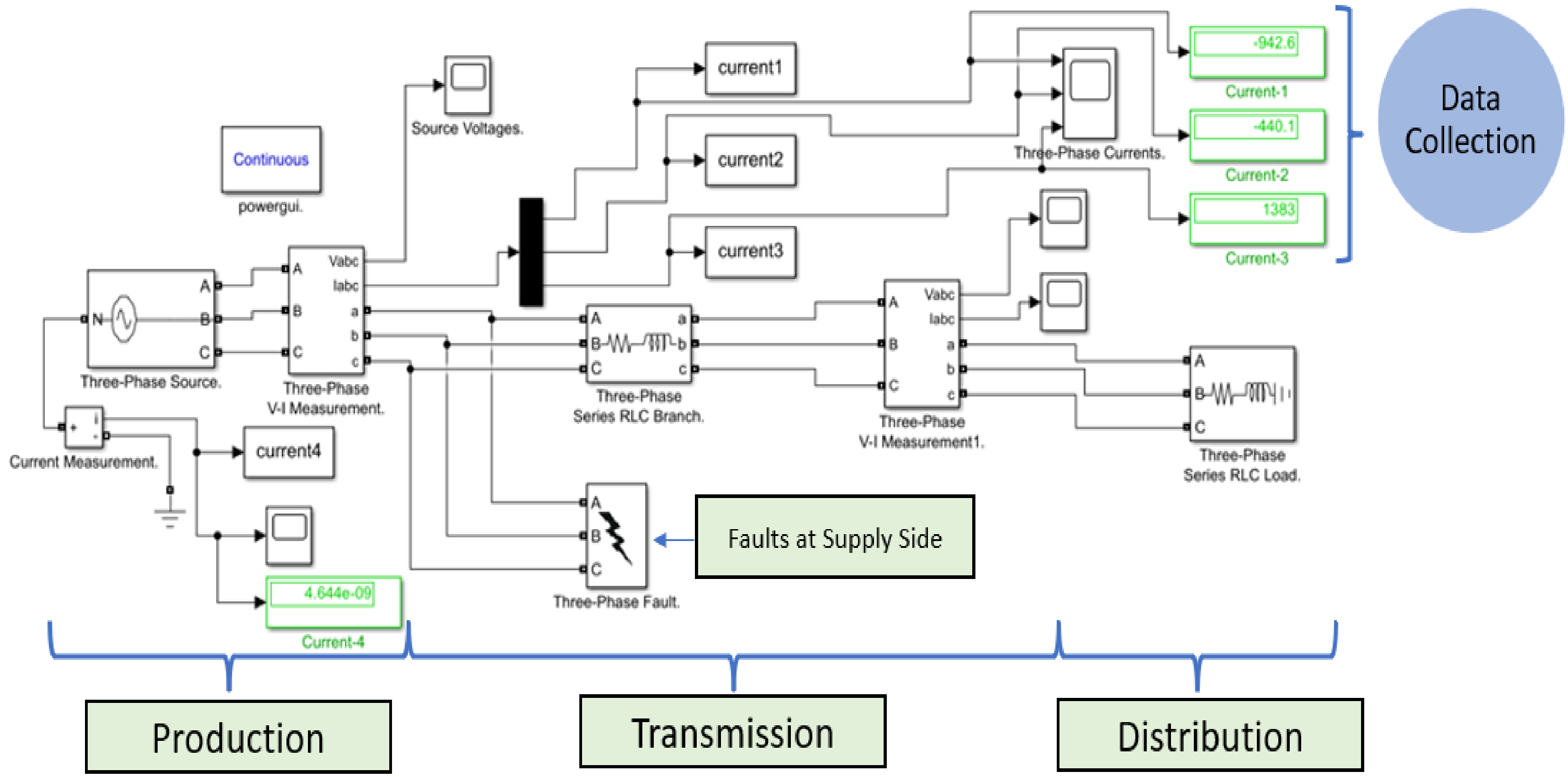



Figure 4-1: Electrical System Model for Fault Calculation

For the collection of current data, there is a need to change the ground resistance and fault condition on a three-phase system as shown in Figure 4-1. According to each phase current value, there is a need to assign the value of 1 for faulty condition and 0 for normal condition as shown in Table 4-1. As we already discussed, larger the dataset has larger the accuracy, that's why by changing the type of fault and ground resistance, 140 cases of different dataset is achieved, 15 cases are shown in the Table 4-1. The maximum threshold value for the coefficients of phase currents is 103.9, which is considered as a normal or good condition, and for ground currents is very less in decimals like 0.02. After implementing the training of NN and setting a goal of zero, the successful training is achieved as shown in Table 4-1.

Table 4-1: Input and Output testing and training data for Neural Network

| S. No. | Type of Fault | Max. coefficient of Phase A Current | Max. coefficient of Phase B Current | Max. coefficient of Phase C Current | Max. coefficient of Ground Current | Output Value for Phase A | Output Value for Phase B | Output Value for Phase C | Output Value for Ground Current |
|---|---|---|---|---|---|---|---|---|---|
| 1 | ABC-G Fault | 1.6097e+07 | 4.0725e+07 | 1.6097e+07 | 7.1824e+05 | 1 | 1 | 1 | 1 |
| 2 | ABC Fault | 1.6097e+07 | 4.0725e+07 | 1.6097e+07 | 0.0081 | 1 | 1 | 1 | 0 |
| 3 | AB-G Fault | 1.0796e+07 | 2.1332e+07 | 103.9772 | 7.7574e+05 | 1 | 1 | 0 | 1 |
| 4 | AC-G Fault | 1.9807e+07 | 103.9772 | 8.6730e+06 | 1.9393e+06 | 1 | 0 | 1 | 1 |
| 5 | BC-G Fault | 103.9784 | 4.0725e+07 | 8.1478e+06 | 9.7619e+05 | 0 | 1 | 1 | 1 |
| 6 | A-B Fault | 1.0794e+07 | 2.0363e+07 | 103.9772 | 0.0087 | 1 | 1 | 0 | 0 |
| 7 | A-C Fault | 2.0363e+07 | 103.9772 | 8.6153e+06 | 0.0204 | 1 | 0 | 1 | 0 |
| 8 | B-C Fault | 103.9784 | 4.0725e+07 | 7.2573e+06 | 0.0100 | 0 | 1 | 1 | 0 |
| 9 | A-G Fault | 1.3523e+06 | 103.9772 | 103.9772 | 1.6087e+06 | 1 | 0 | 0 | 1 |
| 10 | B-G Fault | 103.9784 | 3.7024e+06 | 134.3960 | 1.1253e+06 | 0 | 1 | 0 | 1 |
| 11 | C-G Fault | 103.9784 | 103.9772 | 1.4099e+06 | 3.7023e+06 | 0 | 0 | 1 | 1 |
| 12 | No Fault | 103.9784 | 103.9772 | 103.9772 | 7.1737e-10 | 0 | 0 | 0 | 0 |
| 13 | ABC-G Fault | 1.6097e+07 | 4.0725e+07 | 1.6097e+07 | 1.5785e+05 | 1 | 1 | 1 | 1 |
| 14 | ABC Fault | 1.6097e+07 | 4.0725e+07 | 1.6097e+07 | 0.0081 | 1 | 1 | 1 | 0 |
| 15 | AB-G Fault | 7.8178e+06 | 2.0564e+07 | 103.9772 | 1.6470e+05 | 1 | 1 | 0 | 1 |

Now, there are 140 total cases, and for the testing and training of neural network, normally the is a ratio of 30% data for testing and 70% data for training. For better accuracy, there is a need to divide the data, and for training of data must contain some cases closely to testing data.

| **MATLAB Command for Training the data of NN** | **MATLAB Command for Testing the data of NN** |
|---|---|
| I = Input';<br>T = Output';<br>goal = 0.0;*%Minimum error*<br>spread = 1; *%Maximum efficiency*<br>net = newrb(I,T,goal,spread);% *newrb adds neurons to the hidden layer of a radial basis network until it meets the specified mean squared error goal.* | P = Testingdata'<br>Y = sim(net,P)*%sim is the command, which is used to simulates the specified model, which is already build during the training of neural network.*<br>O = Y'*%Output in a column form* |

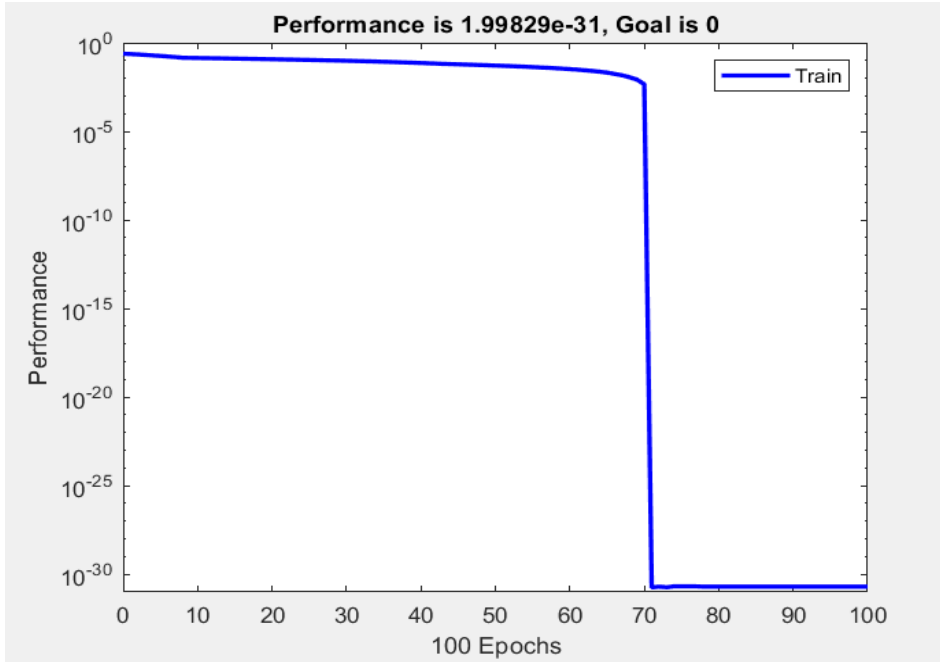



Figure 4-2: Training of Neural Network

After implementing the testing and training of dataset using neural network codes, the output results are achieved, which are shown in the following Table 4-2.

Table 4-2: Comparison of Neural Network Output with actual output values.

| S. No. | Type of Fault | Actual Output Value for Phase A | Actual Output Value for Phase B | Actual Output Value for Phase C | Actual Output Value for Ground Current | NN Output for Phase A | NN Output for Phase B | NN Output for Phase C | NN Output for Ground Current |
|---|---|---|---|---|---|---|---|---|---|
| 1 | ABC-G Fault | 1 | 1 | 1 | 1 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| 2 | ABC Fault | 1 | 1 | 1 | 0 | 1.0000 | 1.0000 | 1.0000 | -0.0000 |
| 3 | AB-G Fault | 1 | 1 | 0 | 1 | 1.0000 | 1.0000 | -0.0000 | 1.0000 |
| 4 | AC-G Fault | 1 | 0 | 1 | 1 | 1.0000 | -0.0000 | 1.0000 | 1.0000 |
| 5 | BC-G Fault | 0 | 1 | 1 | 1 | -0.0000 | 1.0000 | 1.0000 | 1.0000 |
| 6 | A-B Fault | 1 | 1 | 0 | 0 | 1.0000 | 1.0000 | -0.0000 | -0.0000 |
| 7 | A-C Fault | 1 | 0 | 1 | 0 | 1.0000 | 0 | 1.0000 | -0.0000 |
| 8 | B-C Fault | 0 | 1 | 1 | 0 | -0.0000 | 1.0000 | 1.0000 | 0 |
| 9 | A-G Fault | 1 | 0 | 0 | 1 | 1.0000 | -0.0000 | -0.0000 | 1.0000 |
| 10 | B-G Fault | 0 | 1 | 0 | 1 | -0.0000 | 1.0000 | -0.0000 | 1.0000 |
| 11 | C-G Fault | 0 | 0 | 1 | 1 | -0.0000 | -0.0000 | 1.0000 | 1.0000 |
| 12 | No Fault | 0 | 0 | 0 | 0 | -0.0000 | -0.0000 | -0.0000 | -0.0000 |
| 13 | ABC-G Fault | 1 | 1 | 1 | 1 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| 14 | ABC Fault | 1 | 1 | 1 | 0 | 1.0000 | 1.0000 | 1.0000 | -0.0000 |
| 15 | AB-G Fault | 1 | 1 | 0 | 1 | 1.0000 | 1.0000 | -0.0000 | 1.0000 |

After compare the values of output from neural network and the actual output values, it’s determined that, all values are same. That’s why, neural network is an efficient technique to find the and classify the faults and classification of neural networks.

### 4.1.2 Fault Detection at Load Side in Electrical Network

To measure the faults at the load (Consumer's) side, it's essential to attached three phase fault builder at the load side to calculate and record the data at different faulty conditions. In Figure 4-3, there is a 3-phase electrical network, to find the fault at different conditions, there is a need to calculate the data at different faulty conditions and then use that data for the neural network training and testing which is shown in Table 4-3. After implementing the neural network to train the 30% data, the performance and goal curve is achieved, which is shown in Figure 4-4, it means the error in our training is 0.02 which is very close to zero, and represents that the training is successful. After the successful training there is testing process, after implementing the code of testing, the achieved results shows in Table 4-4, which represents that our calculated data and achieved data is same just a 0.02 percent is error in 4rth and 5$^{th}$ serial number fault, which shows the 0.5 numerical values, that is happen due to less data for training of neural network.

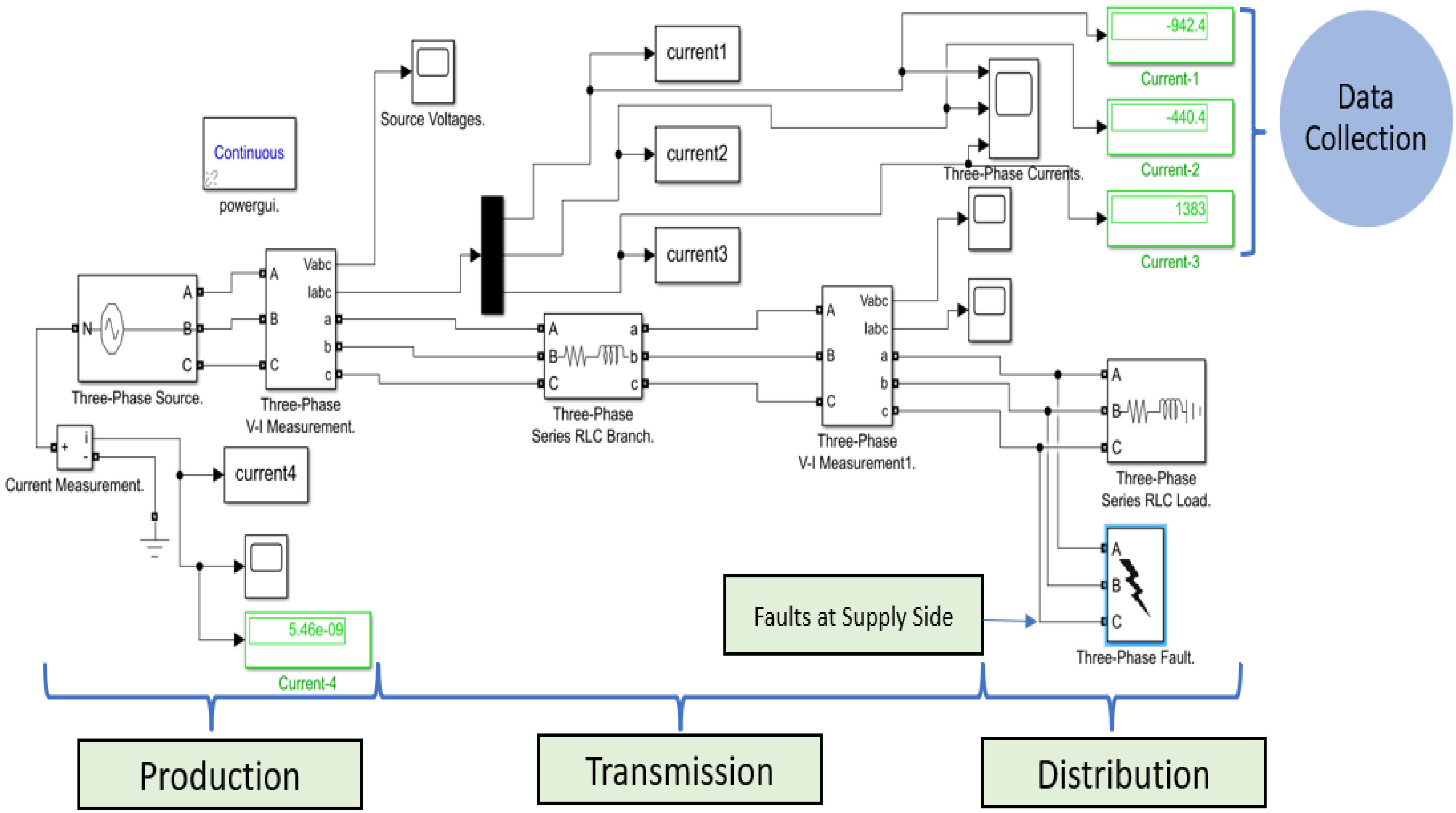



Figure 4-3: Electrical System Model for Fault Calculation

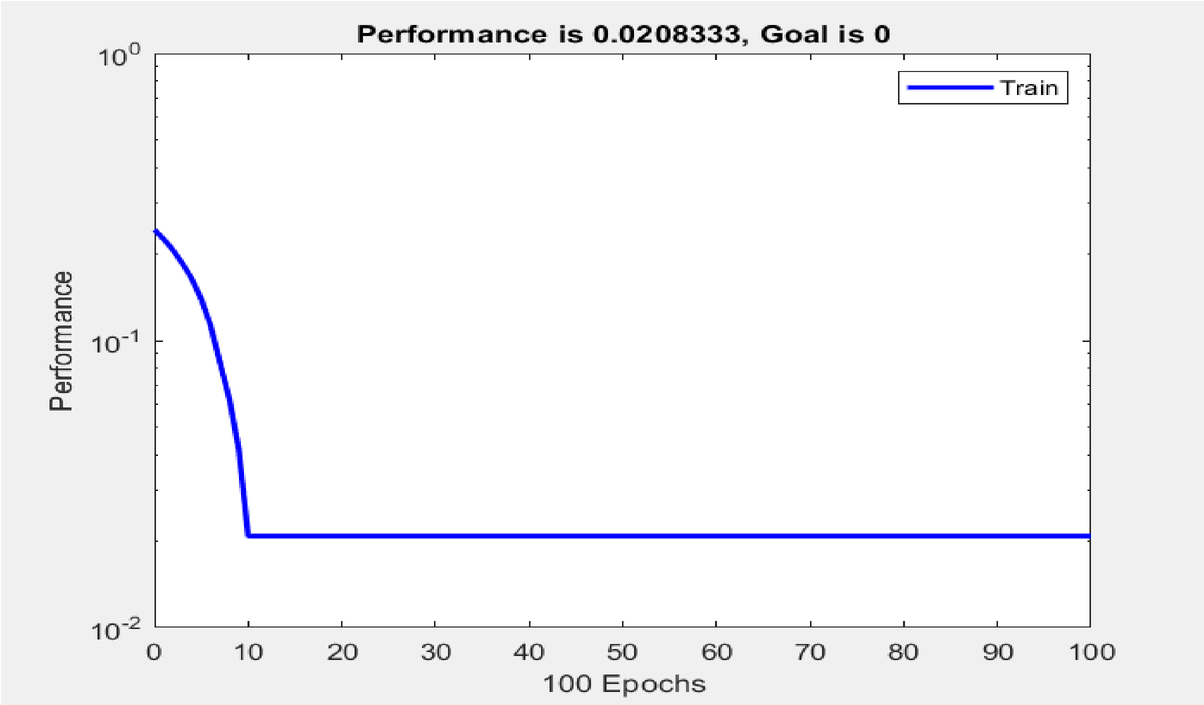



Figure 4-4: Training of Neural Network

Table 4-3: Input and Output testing and training data for Neural Network

| S. No. | Type of Fault | Max. coefficient of Phase A Current | Max. coefficient of Phase B Current | Max. coefficient of Phase C Current | Max. coefficient of Ground Current | Output Value for Phase A | Output Value for Phase B | Output Value for Phase C | Output Value for Ground Current |
|---|---|---|---|---|---|---|---|---|---|
| 1 | ABC-G Fault | 767.3107 | 734.2948 | 792.7979 | 6.1452e-09 | 1 | 1 | 1 | 1 |
| 2 | ABC Fault | 752.7850 | 713.5093 | 779.5074 | 5.1682e-04 | 1 | 1 | 1 | 0 |
| 3 | AB-G Fault | 1.0282e+03 | 807.0932 | 112.4776 | 395.8047 | 1 | 1 | 0 | 1 |
| 4 | AC-G Fault | 881.2649 | 128.1626 | 888.0458 | 500.0681 | 1 | 0 | 1 | 1 |
| 5 | BC-G Fault | 881.2649 | 128.1626 | 888.0458 | 500.0681 | 0 | 1 | 1 | 1 |
| 6 | A-B Fault | 840.8828 | 738.4873 | 118.7332 | 0.0314 | 1 | 1 | 0 | 0 |
| 7 | A-C Fault | 728.3350 | 110.4826 | 894.9877 | 0.0108 | 1 | 0 | 1 | 0 |
| 8 | B-C Fault | 105.5903 | 804.9774 | 703.1693 | 0.0079 | 0 | 1 | 1 | 0 |
| 9 | A-G Fault | 1.0397e+03 | 97.2940 | 121.5884 | 690.7148 | 1 | 0 | 0 | 1 |
| 10 | B-G Fault | 124.9663 | 639.3719 | 85.0469 | 910.1870 | 0 | 1 | 0 | 1 |
| 11 | C-G Fault | 117.0475 | 121.3114 | 799.0698 | 839.8093 | 0 | 0 | 1 | 1 |
| 12 | No Fault | 93.1893 | 115.6854 | 118.7332 | 1.1231e-09 | 0 | 0 | 0 | 0 |
| 13 | ABC-G Fault | 767.3107 | 734.2948 | 792.7979 | 6.1452e-09 | 1 | 1 | 1 | 1 |
| 14 | ABC Fault | 752.7850 | 713.5093 | 779.5074 | 5.1682e-04 | 1 | 1 | 1 | 0 |
| 15 | AB-G Fault | 1.0282e+03 | 807.0932 | 112.4776 | 395.8047 | 1 | 1 | 0 | 1 |

Table 4-4: Comparison of Neural Network Output with actual output values.

| S. No. | Type of Fault | Actual Output Value for Phase A | Actual Output Value for Phase B | Actual Output Value for Phase C | Actual Output Value for Ground Current | NN Output for Phase A | NN Output for Phase B | NN Output for Phase C | NN Output for Ground Current |
|---|---|---|---|---|---|---|---|---|---|
| 1 | ABC-G Fault | 1 | 1 | 1 | 1 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| 2 | ABC Fault | 1 | 1 | 1 | 0 | 1.0000 | 1.0000 | 1.0000 | 0.0000 |
| 3 | AB-G Fault | 1 | 1 | 0 | 1 | 1.0000 | 1.0000 | 0.0000 | 1.0000 |
| 4 | AC-G Fault | 1 | 0 | 1 | 1 | 0.5000 | 0.5000 | 1.0000 | 1.0000 |
| 5 | BC-G Fault | 0 | 1 | 1 | 1 | 0.5000 | 0.5000 | 1.0000 | 1.0000 |
| 6 | A-B Fault | 1 | 1 | 0 | 0 | 1.0000 | 1.0000 | 0.0000 | 0.0000 |
| 7 | A-C Fault | 1 | 0 | 1 | 0 | 1.0000 | 0.0000 | 1.0000 | 0.0000 |
| 8 | B-C Fault | 0 | 1 | 1 | 0 | 0.0000 | 1.0000 | 1.0000 | 0.0000 |
| 9 | A-G Fault | 1 | 0 | 0 | 1 | 1.0000 | 0.0000 | 0.0000 | 1.0000 |
| 10 | B-G Fault | 0 | 1 | 0 | 1 | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| 11 | C-G Fault | 0 | 0 | 1 | 1 | 0.0000 | 0.0000 | 1.0000 | 1.0000 |
| 12 | No Fault | 0 | 0 | 0 | 0 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| 13 | ABC-G Fault | 1 | 1 | 1 | 1 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| 14 | ABC Fault | 1 | 1 | 1 | 0 | 1.0000 | 1.0000 | 1.0000 | 0.0000 |
| 15 | AB-G Fault | 1 | 1 | 0 | 1 | 1.0000 | 1.0000 | 0.0000 | 1.0000 |

## 4.2 Neural Network implementation for energy fraud detection in electrical networks

In recent years, data mining and machine learning (ML) techniques have been used to recognize the patterns of normal and abnormal behavior on the power system network. In this topic, a novel ML technique is proposed to detect energy fraud which can improve the demand side energy management (DSEM) reliability and accuracy.

This can be achieved by obtaining the energy consumption data and analyzing it via implementing an artificial neural network (ANN) algorithm over a pre-determined interval period. There are different topologies of ANN algorithm have been compared and validated to be used for data analysis of the grid. From which Ensemble Bagged Trees has shown 99.7% accuracy as compared to Simple Tree (94.7%) and Logistic Regression (72.4%) topologies. The main advantage of ANN proposed technique is that, it is 20% more accurate, faster detecting to recognize the unauthorised energy user's activities especially for those customers who use renewable energy sources (RES) and grid energy for infrequent intervals of time.

By detecting energy fraud, the efficiency of the entire system is enhanced by saving energy and its utilization for valuable purposes, which is beneficial for suppliers as well as consumers.

### 4.2.1 Various fraudulent behaviors and proposed techniques of DNN

The electrical network integrates with numerous industrial applications presenting an excess of opportunities to convert the traditional electric power network to one which is more secure, efficient, reliable and optimised, this network is known as a Smart Grid. In this research there is a discussion of energy frauds and threats of energy in customer areas of smart meters as shown in Figure 4-5. A SG must provide complete security to customers as wells two-way wireless communication networks to make the system more efficient and reliable. This research considers the following three Customer fraudulent behaviors:

- Type 1: Customer reports has less energy consumed than really used.
- Type 2: Customers used more energy by bypassing meter and connecting to main line.

- Type 3: Customer used energy from neighbor consumers.

Various techniques that could be used to commit these types of fraud include:

- Smart Meter Bypassing
- Tapping on electric line
- Use of chips in meters to slow down its values and readings

The Artificial Neural Network (ANN) technique of Machine Learning (ML) is useful to observe the customer behaviors over time during many different load conditions [70]. ANN trainable system that an efficient and reliable technique that can recognize patterns based on many different input conditions, therefore it is a suitable method to model individual customer behaviors at different load conditions. The efficiency of the presented techniques is determined by investigating energy consumption data over a period of 3 years with differing load levels. This data is gathered from the different customers during a 3-year period, there are a total 12,000 readings, but this paper shows the some portion of that readings in Table-4-5, explained in relevant section. There are several classifiers in ANN, however in this paper there is a comparison of 3 most efficient classifiers of ANN to in order to determine the optimal method for energy fraud detection, which are the following:

I. Simple Tree
II. Logistic Regression
III. Ensemble Bagged Trees

In detail these classifiers are discussed in relevant sections. This topic is sub divided into five parts, part-1 contains the related work, part-2 demonstrates the initialized data, Part-3 describes the synthesis of data and apply it to the ANN, part-4 analyses the results and finally part-5 presents the conclusions and future direction of this research.

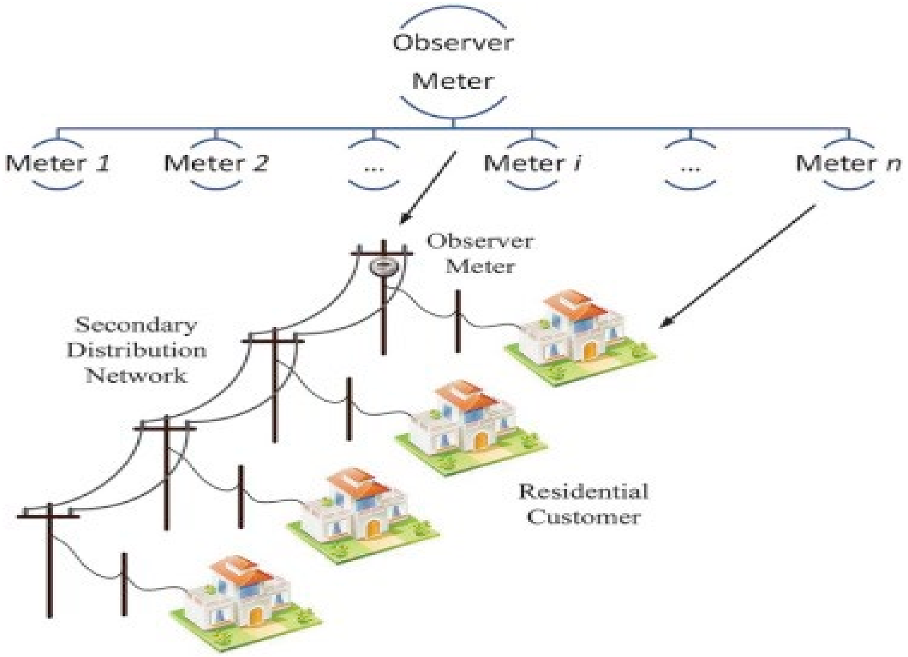



Figure 4-5: Smart meters connection at customer side in SG (Haider et al. 2016)

## 4.3 Data abstraction and Preparation

It is necessary that to analyse the data for computational analysis before the description of artificial neural networks. The data for analysis consists of 12,000 household customers and 3000 business customers. This data is analysed by collecting the readings with the interval of 30 minutes. The data consists of six different files and round about 25 million entries of measure the power ratings.

Its seem that the quality of the output is not only dependent on the ANN algorithm it's also depend on the quality of the data and its analysis which was done previously to measure the readings (Khadse et al. 2021). For measure the better results of energy fraud analysis its seem that the pre data analysis is compulsory 100% pure part of that fraud detection. ANN is the technique of machine learning, which is used to measure the demand response, energy forecasting, distribution energy, energy storage and smart metering, and done IOT based monitoring of data when electrical system integrated with RES.

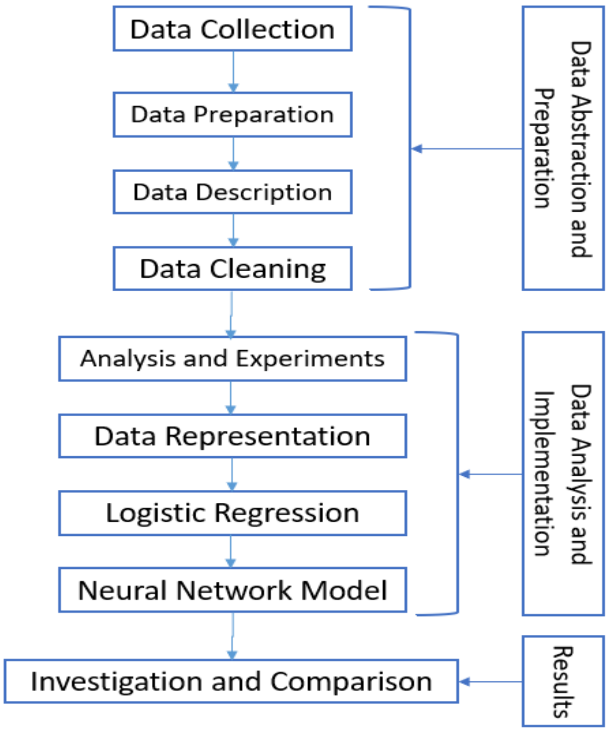



Figure 4-6: Data preparation stages

### 4.3.1 Data Cleaning

Data cleaning is the essential part of the ANN to implement the algorithms for better results and remove the raw data in the beginning of the procedure as shown in flow chart of Figure 4-6. In the beginning the data is measured from the missing values and then measure the energy consumption data and find all missing points which was missed in a prospective spam of time. When we need to find the data of energy values at all missing points, there is a need to verify these values using the daily load curve of energy for different individual customers and overall find the overall energy used in a day at different time spams. After calculating the missing value's, it is compulsory to find the average value of that time spam and put this value as a assumption value to find the best possibilities and implementation of ANN to achieve the desired output (Alimi et al.2020) . There are various stages and layers of ANN to implement it at any data values, and iterations run simultaneously to find the best possible results. The second step of cleaning is used to eliminate the outliers to achieve the best possible solutions (Bravo-Rodríguez et al. 2020). After finding the values and measurements it is essential part to take the mean of all same values to determine the best suitable and optimise set of data for the algorithms of ANN. These values cannot be considered for the fraud detection and specially to find the energy consumption values of customers.

After finding the complete dataset if there is any extra value in the data then its compulsory to remove it from the data, to find the best suitable condition of optimisation and fraud detection (Fadlullah et al. 2013). The ANN algorithm to find these values is shown in Figure 4-7.

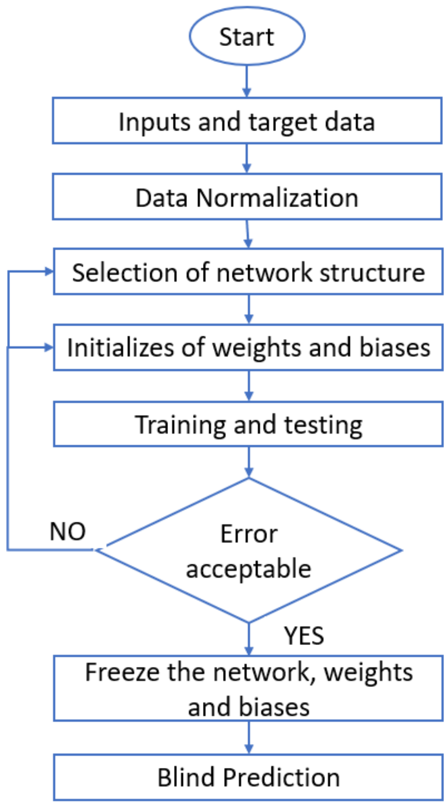



Figure 4-7: ANN algorithm

### 4.3.2 Feature Selection

The smart meter contains a lot of values and parameters such as daily, monthly, or yearly base energy consumption. The features selections in ANN is an important part to find the selected parameters and values which are essential for our experiments of fraud detection. After selection of values, it is an essential to compare these values to achieve the best suitable and possible outcomes, finally use these values for algorithms of ANN.

### 4.3.3 Indexing and Compressing

The millions of entries are mentioned in data files, to find the best possible solution of fraud detection. After that there is a need to compress and separate these data files according to the accuracy of dataset values, which are more useful for fraud detection experiments, because it is not suitable to hold all the files for find the best condition.

## 4.4 Fraud detection approach

To derive the intelligence in each area of research machine learning have a very vast role of implementation and find the best suitable conditions. Specially, for complex systems machine learning have vast benefits to enhance the efficiency of entire system. Due to fast response qualities and better accuracy the artificial neural network (ANN) is the best technique of machine learning (ML) to find the fraud detection the electrical energy system and especially on smart or micro grids. (Sindi 2021; Muthuraman 2021).
The artificial neural network (ANN) consists of three various types of layers to perform the function. The various values of data set of input are included in first layer. The second layer consists of the hidden nodes and various other hidden layers. The third and last layer consists of the output of neural network (Hameed et al. 2021).
The main advantage of using artificial neural network is that to measure all the energy values of all customers and predict the energy demand for future. If there is any deviation in the standard values of each consumer, then it can also be used for energy fraud detection.

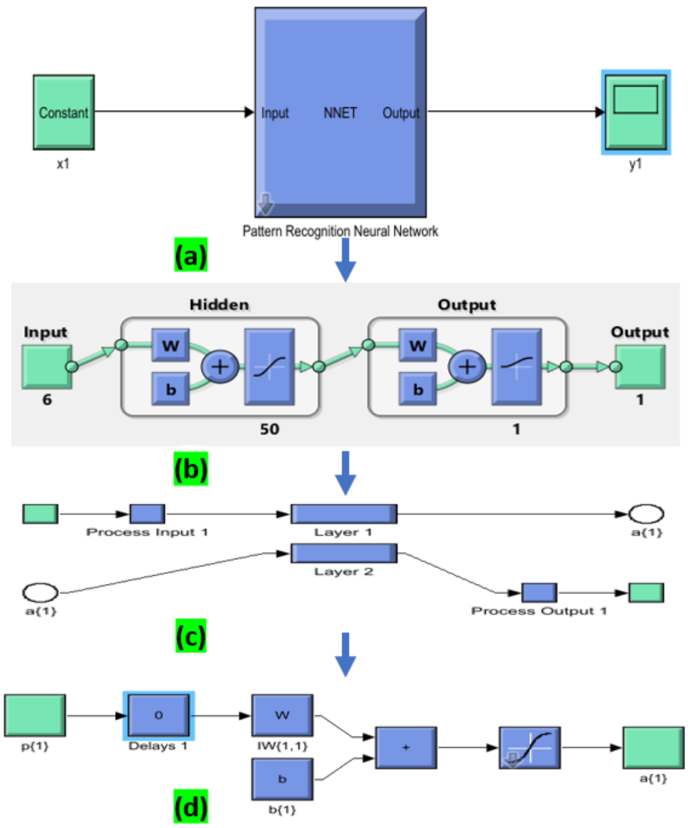



Figure 4-8: (a) ANN Model, (b) Hidden Layers Neuron selection (c) Selected numbers of hidden layers (d) Parameters of each hidden layer

### 4.4.1 Selection of Input/Output Parameters for Neural Network Structure

The input and output parameters are very essential for detect the exact values and results. The hidden layer is modifiable and consist of only one layer in our experiments. The output layer consists of one layer and have the values of smart meter datasets. The input layer consists of the number of consecutive days. Each day consists of 48 dimensions due to meter readings have an interval of 30 minutes of dataset. Therefore, the input layer contains a total number of 48u N nodes. The overall implementation of ANN model is shown in Figure 4-8 step by step from model to parameters selection of hidden layers.

### 4.4.2 Generation of Training and Validation Datasets

In this training there is a complete dataset of values of consumers, and there is an implementation of these values of dataset using ANN for a selected interval of time. For example, to take the dataset of any consumer and check its values for a selected interval of time as for one month. There are lot of values are set according to the ANN algorithm and required experiment and after that check all the experiments and its deviation according to their standard time and deviation. Initially, measure the dataset files, after implementing in the ANN algorithm check the outcomes, if there is a change and deviation occur in the data then its possibilities of fraud occur in the system. The same algorithms and procedures implemented simultaneously on different datasets and observe the outcomes for selected months, weeks, and seasons.

### 4.4.3 Training the Neural Network

For the selected values of dataset ANN is the best one for training its results and its energy behavior for a selected interval of time.

### 4.4.4 Prediction

When task runs using the ANN for the selected values of dataset the output of the neural network will predicts the expected value of data point in the smart meter reading.

### 4.4.5 Detection of Deviation

The best deviation indicator is the Root Mean Squared Error (RMSE (Koutroulis and Kolokotsa 2010) which serves between the predicted value and the actual value in the validation dataset and is calculated as shown in the following equations:

The overall neural network model can be characterised by the following equation (4.1).

$$Y = X_i * W_i + g \tag{4.1}$$

Where $Y$ represents the output, and $X_i$ denotes the set of input values, $W_i$ denotes the connected weights and $g$ represents the activation function applied at each neuron level or layer-specific operation that combines input values and weights. It is used to map the weighted sum of inputs to produce the output $Y$.

Let $X$ be the input to the input layer and can be represent by equation (4.2).

$$X = x_1, x_2, x_3 \dots \dots \dots x_n \tag{4.2}$$

Where $x_1, x_2, x_3 \dots \dots \dots x_n$ denotes the number of inputs from 1 to n.

Its own weights ($W$) for the training can be representing as in equation (4.3).

$$W = W_1, W_2, W_3 \dots \dots \dots W_n \tag{4.3}$$

Where $W$ denotes the weight matrix for the neural network and $W_1, W_2, W_3 \dots \dots \dots W_n$ represent the weight vectors for the n number of layers. For layer-1 the weight vector can be expressed as in equation (4.4).

$$W_1 = w_1, w_2, w_3 \dots \dots \dots w_n \tag{4.4}$$

If the number of hidden layers is equal to n then the bias $B$ represented as in equation (4.5).

$$B = B_1, B_2, B_3 \dots \dots \dots B_n \tag{4.5}$$

The first hidden layer's bias vector value is represented by $B_1$ which shows in equation (4.6).

$$B_1 = b_1, b_2, b_3 \dots \dots \dots b_n \tag{4.6}$$

The net input value ($Z$) for the n number of layers in the neural network which is represented by Z and shows in equation (4.7)

$$Z = Z_1, Z_2, Z_3 \dots \dots \dots Z_n \tag{4.7}$$

Now the first hidden layer's net input ($Z$) can be calculated as shown in equation (4.8).

$$Z(1) = B(1) + \sum((X) * W(1)) \tag{4.8}$$

$A$ be the activation function for individual layers in the neural network and it is represented as shown in equation (4.9). A on the other hand, refers to the output of the activation function at specific layers after applying g to the input values in each layer.

$$A = A_1, A_2, A_3 \dots \dots \dots A_n \quad (4.9)$$

$$A(1) = \frac{1}{1-e^{-Z(1)}} \quad (4.10)$$

Where $A_1, A_2, A_3 \dots \dots \dots A_n$ the activation is function of each hidden layer and can be represented as equation (4.10).

## 4.5 Results Analysis of Proposed Techniques

The Table-4-5 is a sample of the dataset which has been utilized in carrying out this research. The dataset is comprised of 12000 values in which input is three phase currents and voltages and output is binary. Fraud detectection has been characterised as 0 or 1. If there is no fault, it is represented with a 0 value and if there is a fault, it is represented as 1. The ROC curve is a noteworthy tool for making the decision that whether a constraint clearly discriminate among the two groups (i.e. No Fault/Fault). The simulation of results has been done using MATLAB-2021a. The particulars of the constraints which have been tested are given below.

Table-4-5: 10 samples of readings out of 12000 datasets

| Output (Y) | $I_a$ | $I_b$ | $I_c$ | $V_a$ | $V_b$ | $V_c$ |
|---|---|---|---|---|---|---|
| 0 | -43.47472218 | -5.38823325 | 48.86295543 | 0.235732767 | -0.591319681 | 0.355586914 |
| 1 | -37.00645408 | -6.567132402 | 43.57358648 | 0.250284461 | -0.587394985 | 0.337110525 |
| 0 | -40.49158839 | -7.334342845 | 47.82593124 | 0.253680829 | -0.593092855 | 0.339412027 |
| 0 | -38.48959314 | -8.385391735 | 46.87498487 | 0.264396881 | -0.592289668 | 0.327892787 |
| 1 | -40.90712078 | -9.331470657 | 50.23859144 | 0.268902243 | -0.596917687 | 0.328015444 |
| 1 | -35.63892688 | -10.63916237 | 46.27808924 | 0.28209308 | -0.593799269 | 0.311706189 |
| 1 | -37.60265937 | -11.56345398 | 49.16611335 | 0.286978133 | -0.597591493 | 0.31061336 |
| 1 | -35.34843592 | -12.571981 | 47.92041691 | 0.297321281 | -0.596182452 | 0.298861172 |
| 0 | -38.37192616 | -13.30575983 | 51.67768599 | 0.301313491 | -0.600033502 | 0.298720011 |
| 0 | -34.69792544 | -14.32970099 | 49.02762642 | 0.312546754 | -0.597346614 | 0.284799861 |

$$\text{True Positive } (T_P) \text{ Rate} = \frac{T_P}{T_P + F_N} \quad (4.11)$$

$$\text{False Negative } (F_N) \text{ Rate} = \frac{F_N}{F_N + T_P} \quad (4.12)$$

$$\text{Positive predictive value } (P_{PV}) = \frac{T_P}{T_P + F_P} \quad (4.13)$$

$$\text{False Discovery Rate } (F_{DR}) = \frac{F_P}{F_P + T_P} \quad (4.14)$$

$$\text{Accuracy} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N 0} \quad (4.15)$$

- True positives are denoted by $T_P$. It shows the data which are correctly identified as no fault.
- True negatives are denoted by $T_N$. It represents the data which are accurately detected as fault.
- False positives are denoted by $F_P$. the values which are incorrectly identified as no fault.
- False negatives are denoted by $F_N$. it shows the number of data which are incorrectly identified as fault.

The dataset has been fed to three classifiers namely (1) Simple Tree, (2) Logistic Regression and (3) Ensemble Bagged Trees classifier.For all the three classifiers 5 folds cross validation has been applied.

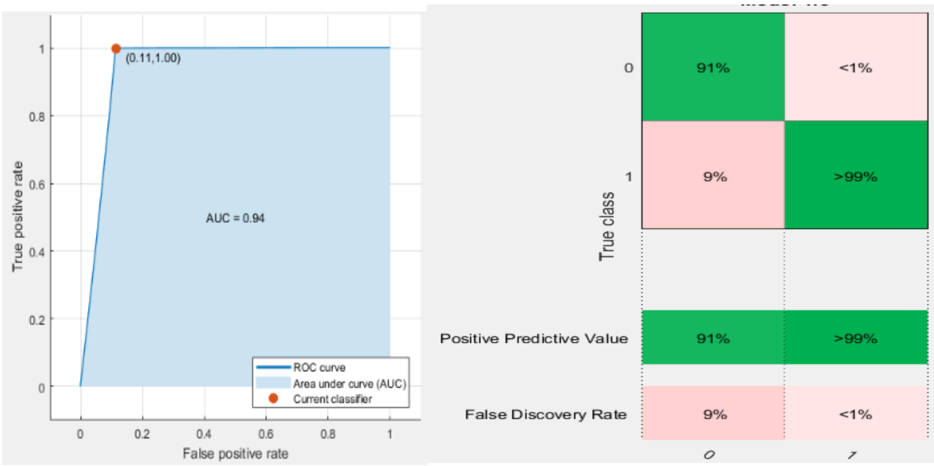



Figure 4-9: Simple tree classifier ROC curve and confusion Matrix


Figure 4-10: Simple tree classifier Confusion Matrix detail

The simple Tree Classifier shows 94.7% accuracy. With 89% true positive rate and 11% False negative rate. The positive predictive value is 91% while the false discovery rate is 9% as shown in Figure 4-9 and Figure 4-10.

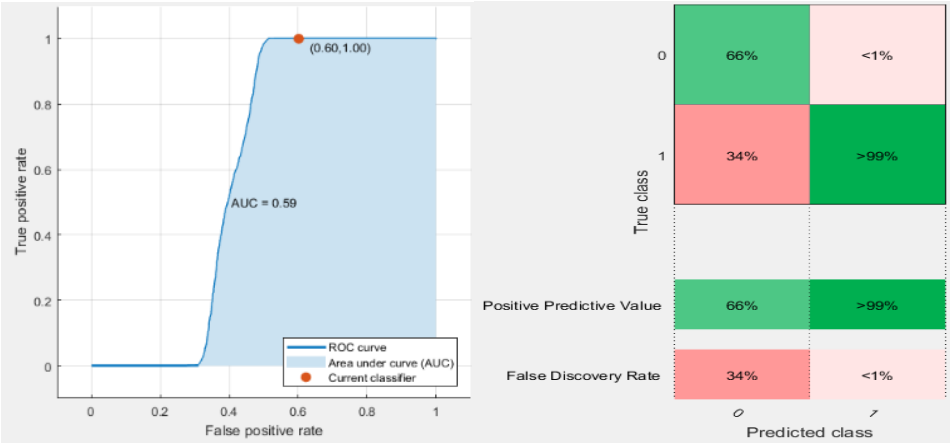



Figure 4-11: Logistic regression classifier ROC curve and Confusion Matrix


Figure 4-12: Logistic regression classifier Confusion Matrix detail

The Logistic Regression Classifier shows 72.4% accuracy with 40% true positive rate and 60% False negative rate. The positive predictive value is 66% while the false discovery rate is 34% as shown in Figure 4-11 and Figure 4-12.

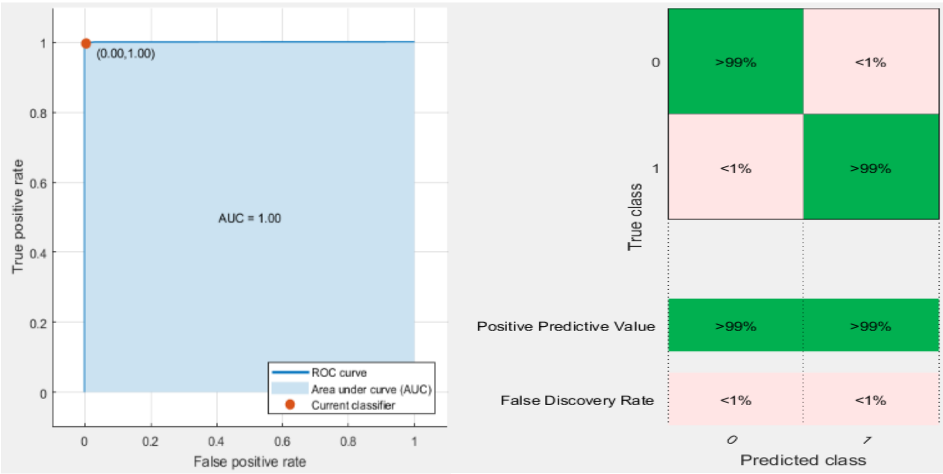



Figure 4-13: Ensemble Bagged Trees classifier ROC curve and Confusion Matrix


Figure 4-14: Ensemble Bagged Trees Classifier Confusion Matrix detail.

The Ensemble Bagged Trees Classifier shows 99.7% accuracy with greater than 99% true positive rate and less than 1% False negative rate. The positive predictive value is greater than 99% while the false discovery rate is less than 1% as shown in Figure 4-13 and Figure 4-14.

The dataset has been then fed to Artificial Neural Network with 10 Neurons and 70% data has been used for training and has been done using Scaled conjugate gradient backpropagation. Validation has been done using 20% data and testing has been done using 10% data. The receiver operating characteristics (ROC) curve has been shown below.

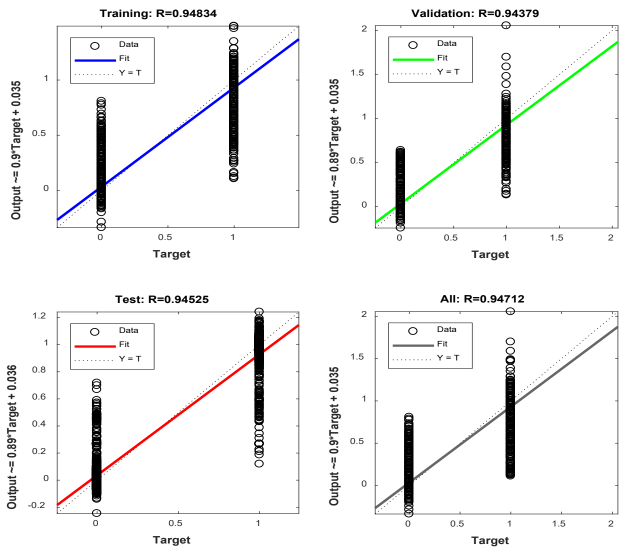



Figure 4-15: Overall ROC Curve by ANN

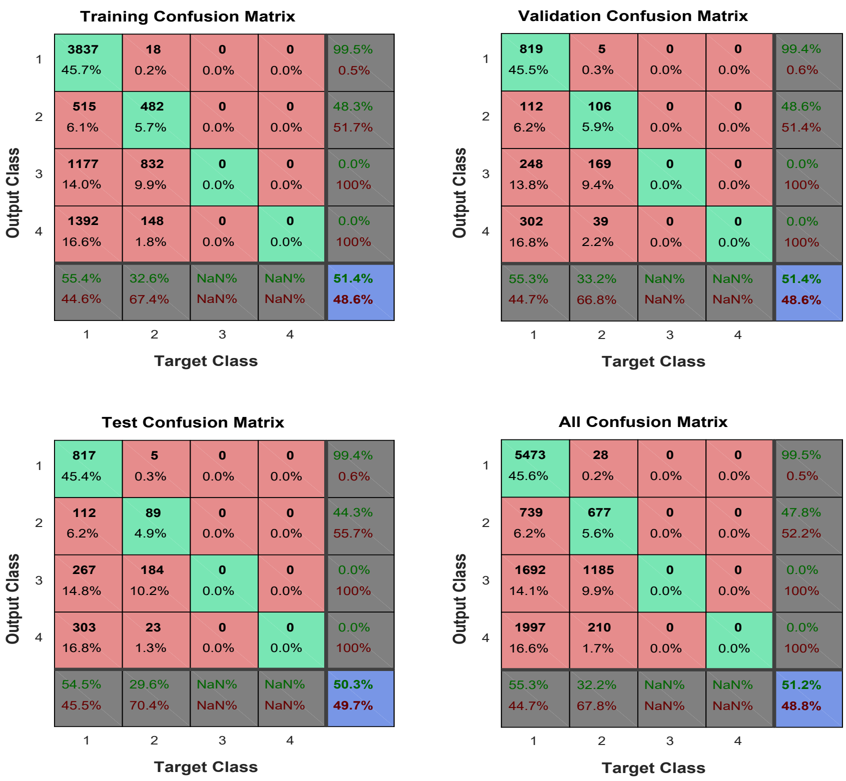



Figure 4-16: Overall Confusion Matrix by ANN

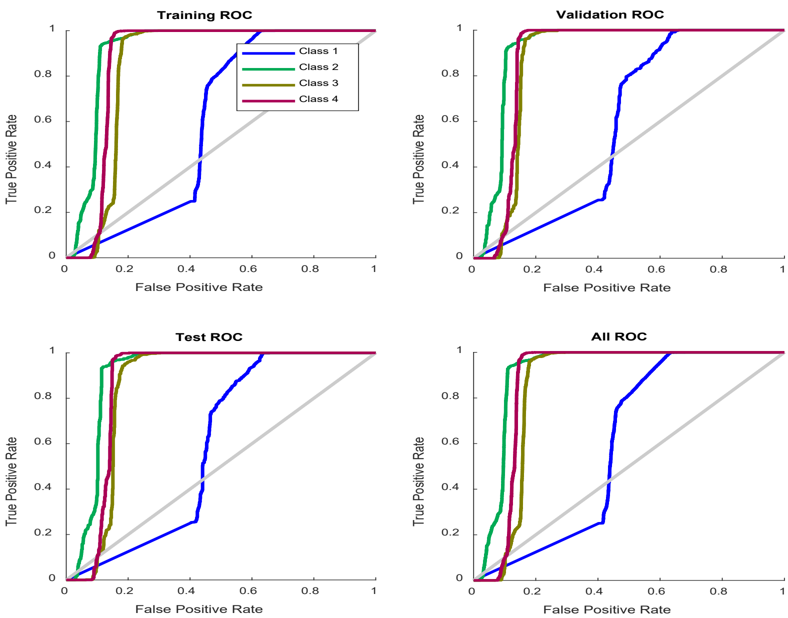



Figure 4-17: Overall Error Histogram by ANN

ROC curve is a plotting between true positive rate and false positive rate to determine the prediction of outcomes as shown in Figure 4-15 and Figure 4-17when the sensitivity of the system will increase's then false positive rate will also be enhanced. The overall confusion matrix of the system is shown in Figure 4-16, which shows all predictive values of the system. The error between target values and predicted values is known as error histogram in ANN for training, validation, and test of the dataset values. These error values represent the difference between target and predicted values and these values could be negative as shown in Figure 4-18.

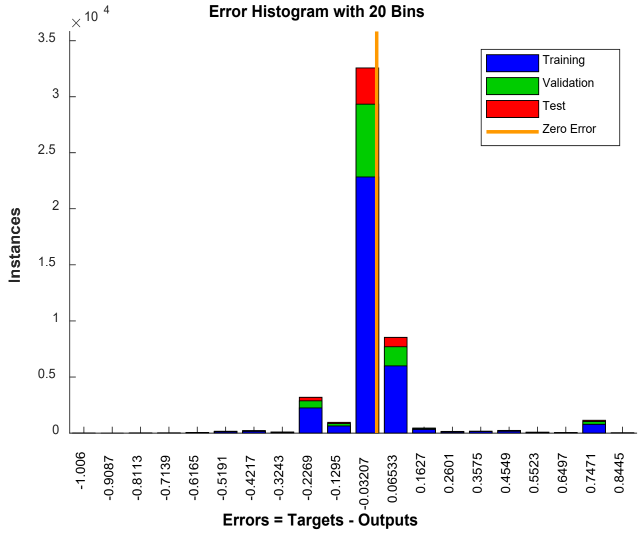



Figure 4-18: Overall learning values

## 4.6 Summary of Chapter

Smart Grid (SG) integrated with renewable energy resources (RES) is an advance stage of traditional grids with two-way power and communication flow, it's the reason there are more chances of energy frauds and cyber-attacks, which are harmful for the entire network. In this research paper there is an implementation of artificial neural network (ANN) technique to detect the fraud detection, when multiple users relate to RES with distribution generation (DG) and grid energy. The ANN approach of machine learning (ML) has best possible results for energy forecasting and especially fraud detection in smart grid. The data monitoring from providers to customer's side is essential part to control the demand side energy management (DSEM) and to observe the behavior of providers to customers profile to control the frauds and cyber-attacks. To detect the fraud activities at different intervals of time at different clusters is much essential to meet the requirement of energy in SG. The results show that, by implementing the ANN technique in three proposed experiments it's an easy to detect the faults from providers to customer side by implementing on specific intervals of time. In this way the DSEM can be control which is suitable to make the entire network of SG more reliable, secure, and efficient.

**Future Directions:**

- Comparison of different techniques of ML can be done to find the best possible outcome.
- By increasing the number of hidden layers, it is possible to achieve more efficiency for huge values of data and complex systems.

# Chapter 5: Implementation of Deep Neural Network-Based Optimisation for Clustered Demand-Side Energy Management in Smart Grids

In this chapter, there is a comprehensive framework for Clustered Demand Side Energy Management (CDEM) by implementing the algorithm of Deep Neural Network (DNN). CDEM aims to optimise energy consumption at customer side, when different types of providers, consumers and prosumers are integrated with electrical system. The key steps for this implementation, including data collection, preprocessing and data clustering. A neural network architecture is designed to predict energy demand for each cluster with the integration of different types of customers (Consumers and Prosumers). The model's effectiveness is validated through various analysis, and it is deployed in real-world energy management scenarios. This holistic approach to CDEM offers the potential for significant energy savings and sustainability improvements, with adaptability to evolving demand patterns.

The global energy landscape is undergoing a profound transformation driven by sustainability imperatives, advances in technology, and changing consumer expectations. The concept of Clustered Demand-Side Energy Management (CDEM) within a Smart Grid framework has emerged as a strategic approach to revolutionize the consumption and management of energy. This paradigm recognizes that energy consumption patterns are highly diverse, influenced by factors such as geographical location, consumer type, weather conditions, and temporal dynamics. Furthermore, the inclusion of prosumers, those who both consume and produce energy, adds a dynamic layer of complexity and opportunity to the smart grid ecosystem.

In this dynamic energy ecosystem, CDEM becomes a linchpin for optimising energy usage, reducing costs, and promoting sustainability. It acknowledges that both consumers and prosumers possess unique energy profiles, and by clustering them intelligently, we can devise tailored strategies that maximize efficiency, grid stability, and sustainability.

**The Smart Grid and Its Role:**

Smart grid is a modern type of electricity grid, that integrates digital technology, advanced communication infrastructure, and intelligent control systems. The Smart Grid represents a departure from the traditional grid infrastructure, enabling real-time monitoring, two-way communication between utilities and consumers, and dynamic control of energy resources. The Smart Grid offers a multitude of benefits, including improved reliability, reduced energy losses, enhanced integration of renewable energy sources, and efficient demand management. It provides the essential data infrastructure required for CDEM, allowing for real-time data collection, analysis, and decision-making.

**The Role of Neural Networks in CDEM:**

Neural Networks plays a vital role for clustered demand side energy management (CDEM) with various types of consumers and prosumers in smart grid. Neural networks are uniquely suited for the task of modelling and predicting complex, time-dependent sequences that characterise energy demand patterns, including those of consumers and prosumers. These computational models, inspired by the structure and function of the human brain, possess the ability to ingest large volumes of data, uncover hidden patterns, and generate accurate and adaptive predictions.

## 5.1 Prediction of Energy for Energy Management

The prediction of energy is an also important part of the energy management, in this section there is the detailed description of energy prediction procedure by implementing the technique of deep neural networks.

**Energy Prediction of 90 Customers:**

In this implementation there are ninety customers are addressed to predict their energy on the daily basis, however energy is taken after each one hour by using the smart meter. There are several different possibilities and types of smart meters to collect the energy data after each fifteen minutes, thirty minutes and one hour. In this implementation there is the prediction of one hour energy data taken of ninety customers. However, if there is a large value of datasets the prediction and accuracy of neural network is more accurate and perfect. The proposed datasets of consumed energy of 26 customers (Total 90 customers) are shown in Table 5-1.

The U.K standardize conditions for energy efficiency measurement of consumers is shown in Figure 5-1, In which there are different classes of energy consumption from A+-G, which differentiation is based on the customers usage of energy (kWh). Class-A+ is the category of that customers who are completely using the RES and have a zero-energy required from grid. Class-A is the category of customers who use the energy from 0-25 kWh, and similarly there are different ratings from B-G as showing in Figure 5-1.

Table 5-1: Proposed dataset for energy prediction of 26 customers out of 90 customers

| 1 | 00:00 | 01:00 | 02:00 | 03:00 | 04:00 | 05:00 | 06:00 | 07:00 | 08:00 | 09:00 | 10:00 | 11:00 | 12:00 | 13:00 | 14:00 | 15:00 | 16:00 | 17:00 | 18:00 | 19:00 | 20:00 | 21:00 | 22:00 | 23:00 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 65 | 62 | 56 | 57 | 58 | 58 | 64 | 70 | 74 | 68 | 67 | 69 | 72 | 67 | 64 | 68 | 66 | 68 | 88 | 86 | 80 | 77 | 73 | 68 |
| 3 | 67 | 61 | 57 | 58 | 57 | 59 | 63 | 71 | 75 | 69 | 67 | 70 | 74 | 68 | 65 | 68 | 72 | 72 | 87 | 83 | 83 | 77 | 77 | 70 |
| 4 | 65 | 61 | 58 | 57 | 58 | 60 | 63 | 69 | 78 | 70 | 68 | 69 | 73 | 70 | 65 | 67 | 68 | 71 | 89 | 86 | 82 | 81 | 77 | 72 |
| 5 | 67 | 63 | 60 | 61 | 60 | 63 | 67 | 70 | 77 | 72 | 69 | 72 | 75 | 69 | 67 | 71 | 72 | 73 | 88 | 85 | 81 | 82 | 79 | 75 |
| 6 | 68 | 62 | 60 | 60 | 58 | 62 | 65 | 68 | 76 | 73 | 72 | 73 | 74 | 73 | 68 | 70 | 71 | 74 | 87 | 86 | 83 | 82 | 79 | 76 |
| 7 | 69 | 100 | 59 | 61 | 61 | 61 | 65 | 71 | 76 | 72 | 72 | 74 | 78 | 74 | 72 | 73 | 77 | 75 | 89 | 88 | 82 | 84 | 80 | 75 |
| 8 | 65 | 60 | 59 | 58 | 58 | 58 | 64 | 69 | 73 | 73 | 71 | 72 | 74 | 71 | 69 | 71 | 73 | 76 | 85 | 85 | 79 | 80 | 76 | 73 |
| 9 | 67 | 61 | 61 | 57 | 59 | 59 | 64 | 71 | 76 | 72 | 70 | 74 | 76 | 72 | 69 | 72 | 74 | 73 | 86 | 86 | 81 | 83 | 80 | 74 |
| 10 | 100 | 99 | 98 | 97 | 96 | 95 | 94 | 93 | 92 | 91 | 90 | 100 | 99 | 98 | 97 | 96 | 95 | 94 | 93 | 92 | 91 | 100 | 99 | 98 |
| 11 | 65 | 62 | 56 | 57 | 58 | 58 | 64 | 70 | 74 | 68 | 67 | 69 | 72 | 67 | 64 | 55 | 66 | 68 | 88 | 86 | 80 | 77 | 73 | 68 |
| 12 | 67 | 61 | 57 | 58 | 57 | 59 | 63 | 71 | 75 | 69 | 67 | 70 | 74 | 68 | 65 | 88 | 72 | 72 | 87 | 83 | 83 | 77 | 77 | 70 |
| 13 | 65 | 61 | 58 | 57 | 58 | 60 | 63 | 69 | 78 | 70 | 68 | 69 | 73 | 70 | 65 | 11 | 68 | 71 | 89 | 86 | 82 | 81 | 77 | 72 |
| 14 | 67 | 63 | 60 | 61 | 60 | 63 | 67 | 70 | 77 | 72 | 69 | 72 | 75 | 69 | 67 | 22 | 72 | 73 | 88 | 85 | 81 | 82 | 79 | 75 |
| 15 | 68 | 62 | 60 | 60 | 58 | 62 | 65 | 68 | 76 | 73 | 72 | 73 | 74 | 73 | 68 | 33 | 71 | 74 | 87 | 86 | 83 | 82 | 79 | 76 |
| 16 | 69 | 62 | 59 | 61 | 61 | 61 | 65 | 71 | 76 | 72 | 72 | 74 | 78 | 74 | 72 | 44 | 77 | 75 | 89 | 88 | 82 | 84 | 80 | 75 |
| 17 | 65 | 60 | 59 | 58 | 58 | 58 | 64 | 69 | 73 | 73 | 71 | 72 | 74 | 71 | 69 | 23 | 73 | 76 | 85 | 85 | 79 | 80 | 76 | 73 |
| 18 | 67 | 61 | 61 | 57 | 59 | 59 | 64 | 71 | 76 | 72 | 70 | 74 | 76 | 72 | 69 | 85 | 74 | 73 | 86 | 86 | 81 | 83 | 80 | 74 |
| 19 | 100 | 99 | 98 | 97 | 96 | 95 | 94 | 93 | 92 | 91 | 90 | 100 | 99 | 98 | 97 | 69 | 95 | 94 | 93 | 92 | 91 | 100 | 99 | 98 |
| 20 | 65 | 62 | 56 | 57 | 58 | 58 | 64 | 70 | 74 | 68 | 67 | 69 | 72 | 67 | 64 | 55 | 66 | 68 | 88 | 86 | 80 | 77 | 73 | 68 |
| 21 | 67 | 61 | 57 | 58 | 57 | 59 | 63 | 71 | 75 | 69 | 67 | 70 | 74 | 68 | 65 | 88 | 72 | 72 | 87 | 83 | 83 | 77 | 77 | 70 |
| 22 | 65 | 61 | 58 | 57 | 58 | 60 | 63 | 69 | 78 | 70 | 68 | 69 | 73 | 70 | 65 | 11 | 68 | 71 | 89 | 86 | 82 | 81 | 77 | 72 |
| 23 | 67 | 63 | 60 | 61 | 60 | 63 | 67 | 70 | 77 | 72 | 69 | 72 | 75 | 69 | 67 | 22 | 72 | 73 | 88 | 85 | 81 | 82 | 79 | 75 |
| 24 | 68 | 62 | 60 | 60 | 58 | 62 | 65 | 68 | 76 | 73 | 72 | 73 | 74 | 73 | 68 | 33 | 71 | 74 | 87 | 86 | 83 | 82 | 79 | 76 |
| 25 | 69 | 62 | 59 | 61 | 61 | 61 | 65 | 71 | 76 | 72 | 72 | 74 | 78 | 74 | 72 | 44 | 77 | 75 | 89 | 88 | 82 | 84 | 80 | 75 |
| 26 | 65 | 60 | 59 | 58 | 58 | 58 | 64 | 69 | 73 | 73 | 71 | 72 | 74 | 71 | 69 | 23 | 73 | 76 | 85 | 85 | 79 | 80 | 76 | 73 |

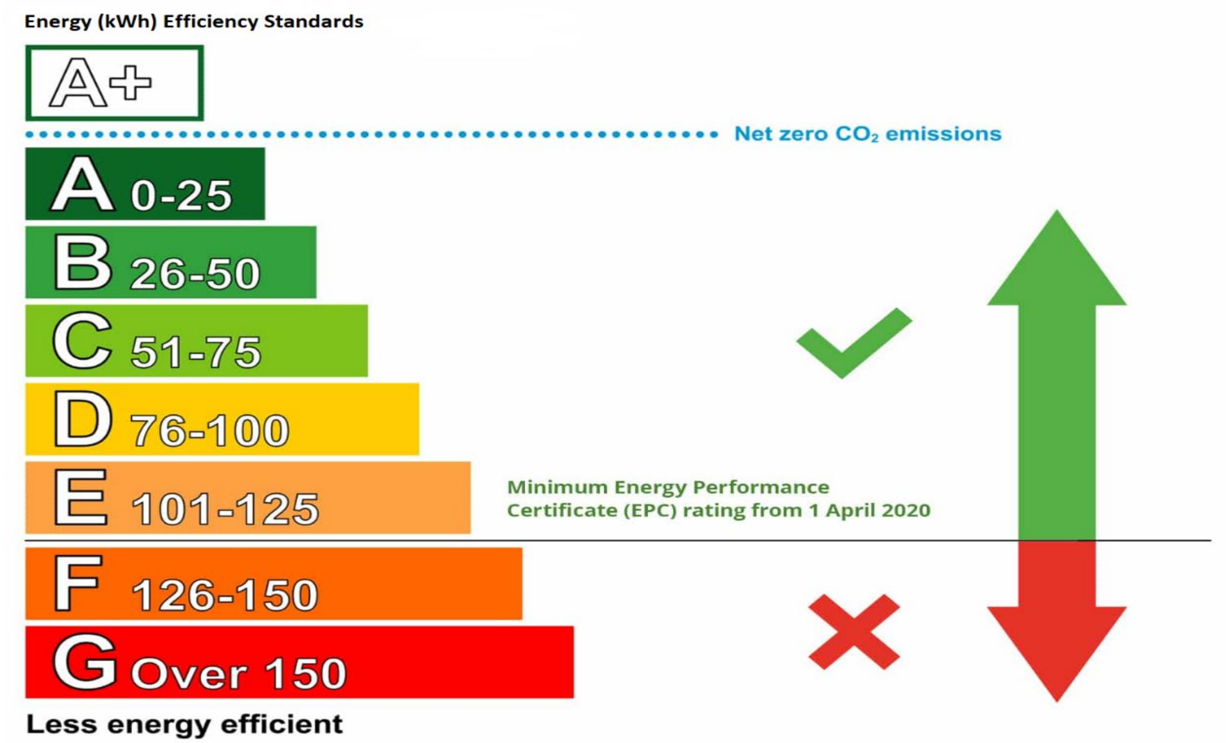



Figure 5-1: Energy (kWh) Efficiency standards at customer's side (Nguyen 2017)

## 5.2 DNN Implementation steps for energy prediction

The procedure to predict the daily energy curve of customers on an hourly basis for the purpose of energy management, and the general phenomenon of implementation is shown in Figure 5-2.

Procedure and steps of implementation to predict the daily load curve are:

1. create a training sample input set,
2. Corresponds to 24 features which is n,
3. Has 90 rows of date which is l,
4. Read the set of data,
5. Create a training set and test set
6. X (Input) train of data set having length l
7. X (Input) test of data set having length l,
8. Y (Output) train of data set having length l,
9. Create Neural Network,
10. Net training of data set,

11. Output training for prediction,
12. Set the minimum convergence error goal of training, which is 0.001,
13. Predict the output (sim (netx test)),
14. Check the root mean square error (sum((Predict-test).^2)/24)^0.5),
15. Check the actual/predicted output curve of prediction,
16. Compare the predictive and Actual values.

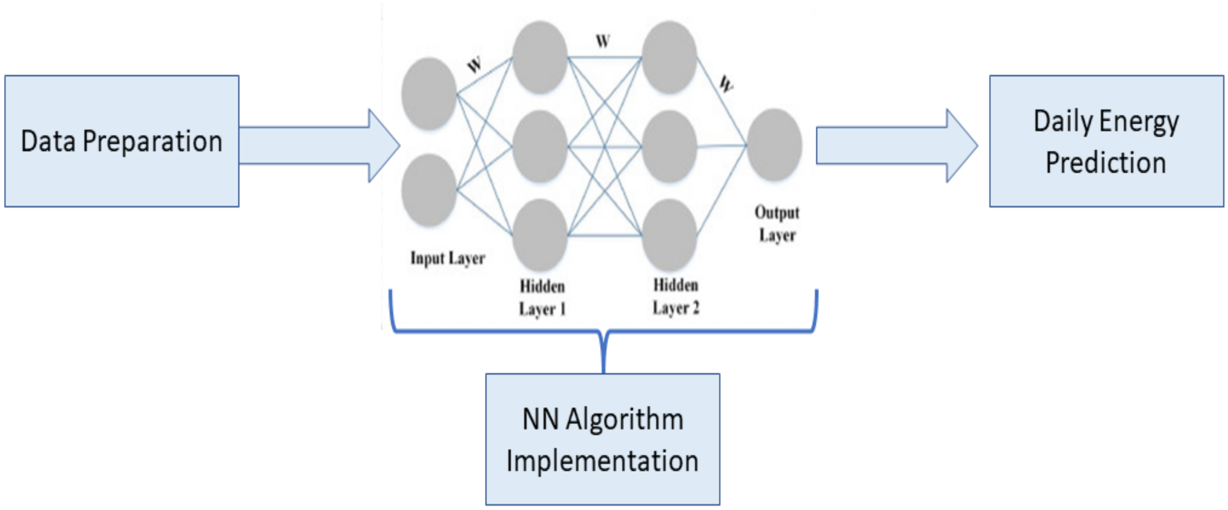



Figure 5-2: Phenomenon of code algorithm implementation for daily load prediction

## 5.3 Discussion and Results (Actual and Predicted Values)

For the implementation of proposed DNN algorithm, there should be a comprehensive dataset for the optimise prediction of energy with respect to proposed customers. In Table 5-2, there is data-head and data-tail is showing of the ninety proposed customers, In which there is a value of consumed energy in kWh during 24-hours of the day. The data is taken after each one hour from the smart meter, which is connected at the consumer's side to measure the consumes energy.

Table 5-2: Data Head & Tail of the proposed dataset

```
data.head()
```

| | 00:00 | 01:00 | 02:00 | 03:00 | 04:00 | 05:00 | 06:00 | 07:00 | 08:00 | 09:00 | ... | 14:00 | 15:00 | 16:00 | 17:00 | 18:00 | 19:00 | 20:00 | 21:00 | 22:00 | 23:00 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 65 | 62 | 56 | 57 | 58 | 58 | 64 | 70 | 74 | 68 | ... | 64 | 68 | 66 | 68 | 88 | 86 | 80 | 77 | 73 | 68 |
| **1** | 67 | 61 | 57 | 58 | 57 | 59 | 63 | 71 | 75 | 69 | ... | 65 | 68 | 72 | 72 | 87 | 83 | 83 | 77 | 77 | 70 |
| **2** | 65 | 61 | 58 | 57 | 58 | 60 | 63 | 69 | 78 | 70 | ... | 65 | 67 | 68 | 71 | 89 | 86 | 82 | 81 | 77 | 72 |
| **3** | 67 | 63 | 60 | 61 | 60 | 63 | 67 | 70 | 77 | 72 | ... | 67 | 71 | 72 | 73 | 88 | 85 | 81 | 82 | 79 | 75 |
| **4** | 68 | 62 | 60 | 60 | 58 | 62 | 65 | 68 | 76 | 73 | ... | 68 | 70 | 71 | 74 | 87 | 86 | 83 | 82 | 79 | 76 |

5 rows × 24 columns

```
data.tail()
```

| | 00:00 | 01:00 | 02:00 | 03:00 | 04:00 | 05:00 | 06:00 | 07:00 | 08:00 | 09:00 | ... | 14:00 | 15:00 | 16:00 | 17:00 | 18:00 | 19:00 | 20:00 | 21:00 | 22:00 | 23:00 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **85** | 68 | 62 | 60 | 60 | 58 | 62 | 65 | 68 | 76 | 73 | ... | 68 | 33 | 71 | 74 | 87 | 86 | 83 | 82 | 79 | 76 |
| **86** | 69 | 62 | 59 | 61 | 61 | 61 | 65 | 71 | 76 | 72 | ... | 72 | 44 | 77 | 75 | 89 | 88 | 82 | 84 | 80 | 75 |
| **87** | 65 | 100 | 59 | 58 | 58 | 58 | 64 | 69 | 73 | 73 | ... | 69 | 23 | 73 | 76 | 85 | 85 | 79 | 80 | 76 | 73 |
| **88** | 67 | 61 | 61 | 57 | 59 | 59 | 64 | 71 | 76 | 72 | ... | 69 | 85 | 74 | 73 | 86 | 86 | 81 | 83 | 80 | 74 |
| **89** | 100 | 99 | 98 | 97 | 96 | 95 | 94 | 93 | 92 | 91 | ... | 97 | 69 | 95 | 94 | 93 | 92 | 91 | 100 | 99 | 98 |

5 rows × 24 columns

K-Fold cross-validation is an effective technique for evaluating the performance of machine learning models, particularly when dealing with limited data. It divides the dataset into **k** equally sized subsets, or "folds," where **k** is a user-defined number, commonly set to 5 or 10. In each of **k** iterations, one fold is used as the test set, and the remaining **k - 1** folds are combined to form the training set. This process continues until each fold has served as the test set once, resulting in **k** different performance scores. These scores are averaged to produce a single metric that provides a more reliable estimate of model performance, as the model is tested across different data splits. This approach not only maximizes the use of the data but also reduces overfitting, as the model is exposed to various data subsets.

Table 5-3: Dataset after K-Fold Cross Validation (Linear Regression Algorithm)

| | 00:00 | 01:00 | 02:00 | 03:00 | 04:00 | 05:00 | 06:00 | 07:00 | 08:00 | 09:00 | ... |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 65 | 61 | 58 | 57 | 58 | 60 | 63 | 69 | 78 | 70 | ... |
| 13 | 68 | 62 | 60 | 60 | 58 | 62 | 65 | 68 | 76 | 73 | ... |
| 53 | 100 | 99 | 98 | 97 | 96 | 95 | 94 | 93 | 92 | 91 | ... |
| 41 | 69 | 62 | 59 | 61 | 61 | 61 | 65 | 71 | 76 | 72 | ... |
| 66 | 67 | 63 | 60 | 61 | 60 | 63 | 67 | 70 | 77 | 72 | ... |
| 30 | 67 | 63 | 60 | 61 | 60 | 63 | 67 | 70 | 77 | 72 | ... |
| 45 | 65 | 62 | 56 | 57 | 58 | 58 | 64 | 70 | 74 | 68 | ... |
| 43 | 67 | 61 | 61 | 57 | 59 | 59 | 64 | 71 | 76 | 72 | ... |
| 78 | 65 | 100 | 59 | 58 | 58 | 58 | 64 | 69 | 73 | 73 | ... |
| 89 | 100 | 99 | 98 | 97 | 96 | 95 | 94 | 93 | 92 | 91 | ... |
| 7 | 67 | 61 | 61 | 57 | 59 | 59 | 64 | 71 | 76 | 72 | ... |
| 26 | 100 | 99 | 98 | 97 | 96 | 95 | 94 | 93 | 92 | 91 | ... |
| 33 | 65 | 100 | 59 | 58 | 58 | 58 | 64 | 69 | 73 | 73 | ... |
| 63 | 65 | 62 | 56 | 57 | 58 | 58 | 64 | 70 | 74 | 68 | ... |
| 8 | 100 | 99 | 98 | 97 | 96 | 95 | 94 | 93 | 92 | 91 | ... |
| 16 | 67 | 61 | 61 | 57 | 59 | 59 | 64 | 71 | 76 | 72 | ... |
| 24 | 65 | 60 | 59 | 58 | 58 | 58 | 64 | 69 | 73 | 73 | ... |
| 56 | 65 | 61 | 58 | 57 | 58 | 60 | 63 | 69 | 78 | 70 | ... |
| 77 | 69 | 62 | 59 | 61 | 61 | 61 | 65 | 71 | 76 | 72 | ... |
| 42 | 65 | 60 | 59 | 58 | 58 | 58 | 64 | 69 | 73 | 73 | ... |
| 22 | 68 | 62 | 60 | 60 | 58 | 62 | 65 | 68 | 76 | 73 | ... |
| 6 | 65 | 60 | 59 | 58 | 58 | 58 | 64 | 69 | 73 | 73 | ... |
| 61 | 67 | 61 | 61 | 57 | 59 | 59 | 64 | 71 | 76 | 72 | ... |
| 48 | 67 | 63 | 60 | 61 | 60 | 63 | 67 | 70 | 77 | 72 | ... |
| 80 | 100 | 99 | 98 | 97 | 96 | 95 | 94 | 93 | 92 | 91 | ... |
| 54 | 65 | 62 | 56 | 57 | 58 | 58 | 64 | 70 | 74 | 68 | ... |
| 73 | 67 | 61 | 57 | 58 | 57 | 59 | 63 | 71 | 75 | 69 | ... |

| | 14:00 | 15:00 | 16:00 | 17:00 | 18:00 | 19:00 | 20:00 | 21:00 | 22:00 | 23:00 |
|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 65 | 67 | 68 | 71 | 89 | 86 | 82 | 81 | 77 | 72 |
| 13 | 68 | 33 | 71 | 74 | 87 | 86 | 83 | 82 | 79 | 76 |
| 53 | 97 | 69 | 95 | 94 | 93 | 92 | 91 | 100 | 99 | 98 |
| 41 | 72 | 44 | 77 | 75 | 89 | 88 | 82 | 84 | 80 | 75 |
| 66 | 67 | 22 | 72 | 73 | 88 | 85 | 81 | 82 | 79 | 75 |
| 30 | 67 | 22 | 72 | 73 | 88 | 85 | 81 | 82 | 79 | 75 |
| 45 | 64 | 55 | 66 | 68 | 88 | 86 | 80 | 77 | 73 | 68 |
| 43 | 69 | 85 | 74 | 73 | 86 | 86 | 81 | 83 | 80 | 74 |
| 78 | 69 | 23 | 73 | 76 | 85 | 85 | 79 | 80 | 76 | 73 |
| 89 | 97 | 69 | 95 | 94 | 93 | 92 | 91 | 100 | 99 | 98 |
| 7 | 69 | 72 | 74 | 73 | 86 | 86 | 81 | 83 | 80 | 74 |
| 26 | 97 | 69 | 95 | 94 | 93 | 92 | 91 | 100 | 99 | 98 |
| 33 | 69 | 23 | 73 | 76 | 85 | 85 | 79 | 80 | 76 | 73 |
| 63 | 64 | 55 | 66 | 68 | 88 | 86 | 80 | 77 | 73 | 68 |
| 8 | 97 | 96 | 95 | 94 | 93 | 92 | 91 | 100 | 99 | 98 |
| 16 | 69 | 85 | 74 | 73 | 86 | 86 | 81 | 83 | 80 | 74 |
| 24 | 69 | 23 | 73 | 76 | 85 | 85 | 79 | 80 | 76 | 73 |
| 56 | 65 | 11 | 68 | 71 | 89 | 86 | 82 | 81 | 77 | 72 |
| 77 | 72 | 44 | 77 | 75 | 89 | 88 | 82 | 84 | 80 | 75 |
| 42 | 69 | 23 | 73 | 76 | 85 | 85 | 79 | 80 | 76 | 73 |
| 22 | 68 | 33 | 71 | 74 | 87 | 86 | 83 | 82 | 79 | 76 |
| 6 | 69 | 71 | 73 | 76 | 85 | 85 | 79 | 80 | 76 | 73 |
| 61 | 69 | 85 | 74 | 73 | 86 | 86 | 81 | 83 | 80 | 74 |
| 48 | 67 | 22 | 72 | 73 | 88 | 85 | 81 | 82 | 79 | 75 |
| 80 | 97 | 69 | 95 | 94 | 93 | 92 | 91 | 100 | 99 | 98 |
| 54 | 64 | 55 | 66 | 68 | 88 | 86 | 80 | 77 | 73 | 68 |
| 73 | 65 | 88 | 72 | 72 | 87 | 83 | 83 | 77 | 77 | 70 |

For the implementation of neural network algorithm, K-Fold cross validation is used in the linear regression algorithm. K-fold cross-validation is a widely used technique for evaluating the execution of machine learning models, including linear regression. It helps to obtain a more accurate estimate of a model's execution by dividing the dataset into k subsets (or folds) and training the model k times, using different subsets as the test set in each iteration. After implementation of K-Fold cross validation by linear regression, the dataset is showing in Table 5-3.

MAE (Mean Absolute Error) is the average of the absolute differences between the predicted values and the actual values. It gives the measure of the average magnitude of errors in predictions without considering their direction. A smaller MAE indicates a better fit of the model to the data.

MSE (Mean Squared Error) is the average of the squares of the differences between the predicted values and the actual values. MSE gives more weight to large errors, making it particularly useful when large errors are undesirable. Like MAE, a smaller MSE indicates a better fit of the model to the data. After implementation the linear regression DNN algorithm, the MAE and MSE values are shown in Figure 5-3. The results of actual and predicted values for the proposed set of data is showing from Figure 5-4 to Figure 5-6 with a regression plot of the overall results. The results shows that the predicted value is always a little bit high as compared to actual values, which is the significant factor for the true prediction at customer's side.

```
MAE: mean = -6.564061463688544e-15 , std = 6.4911017976945325e-15
MSE: mean = -2.1348829983581216e-28 , std = 2.5192162391266467e-28
R2: mean = 1.0 , std = 0.0
```

Figure 5-3: Mean absolute and squared error values after linear regression algorithm

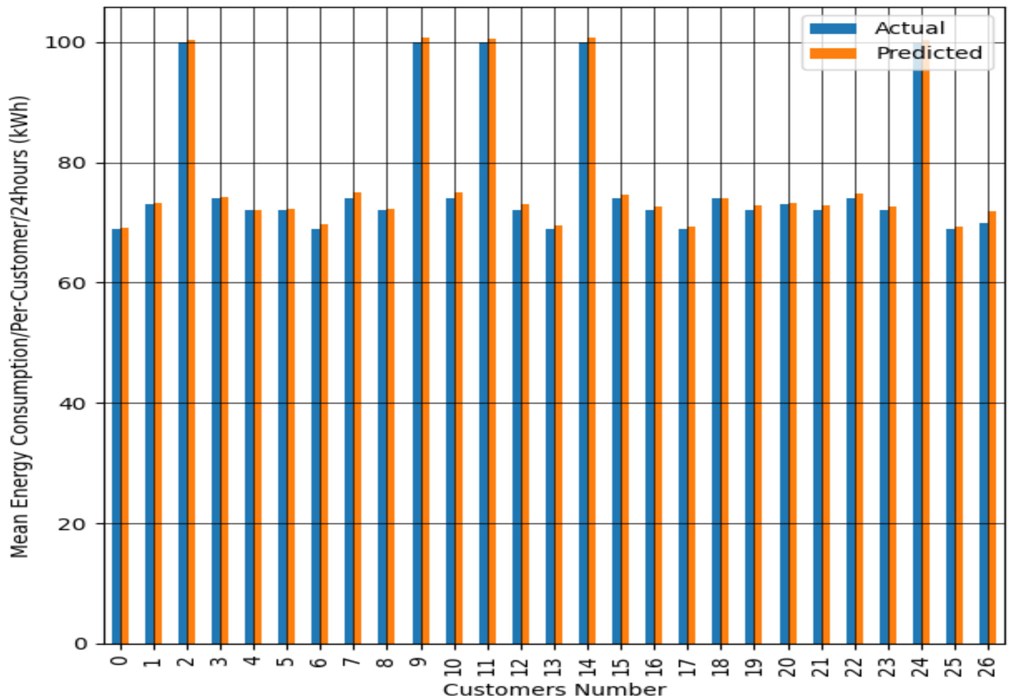



Figure 5-4: Actual and Predicted values bar-chart of the proposed customers

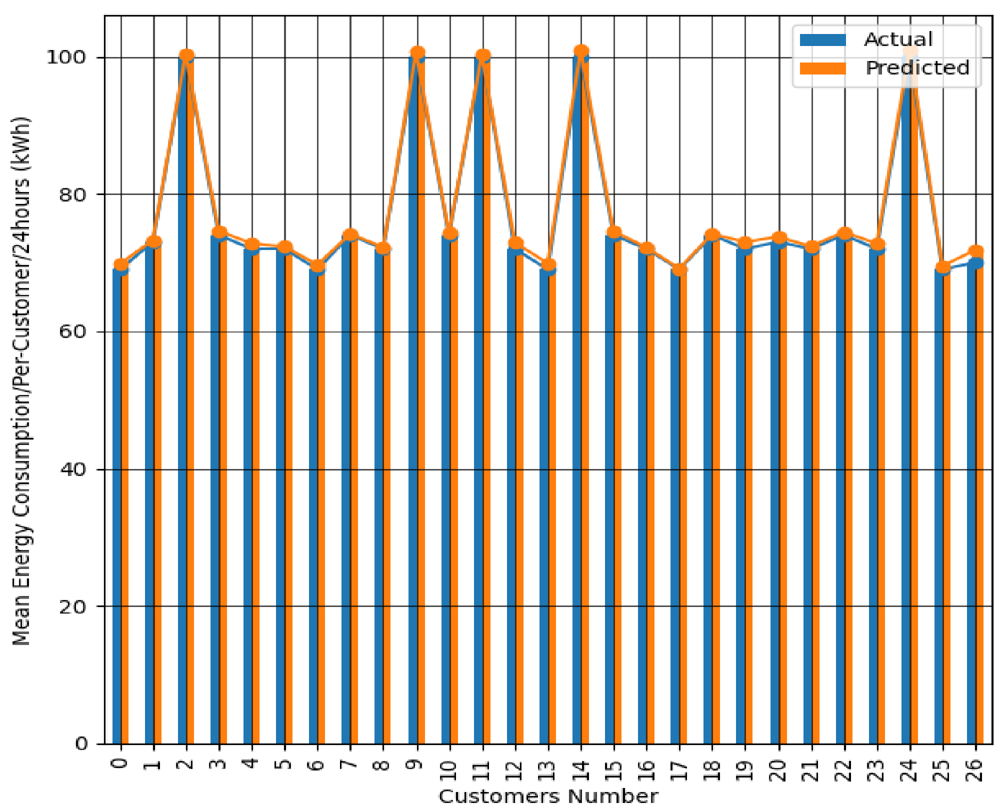



Figure 5-5: Actual and Predicted values bar-chart/curve of the proposed customers

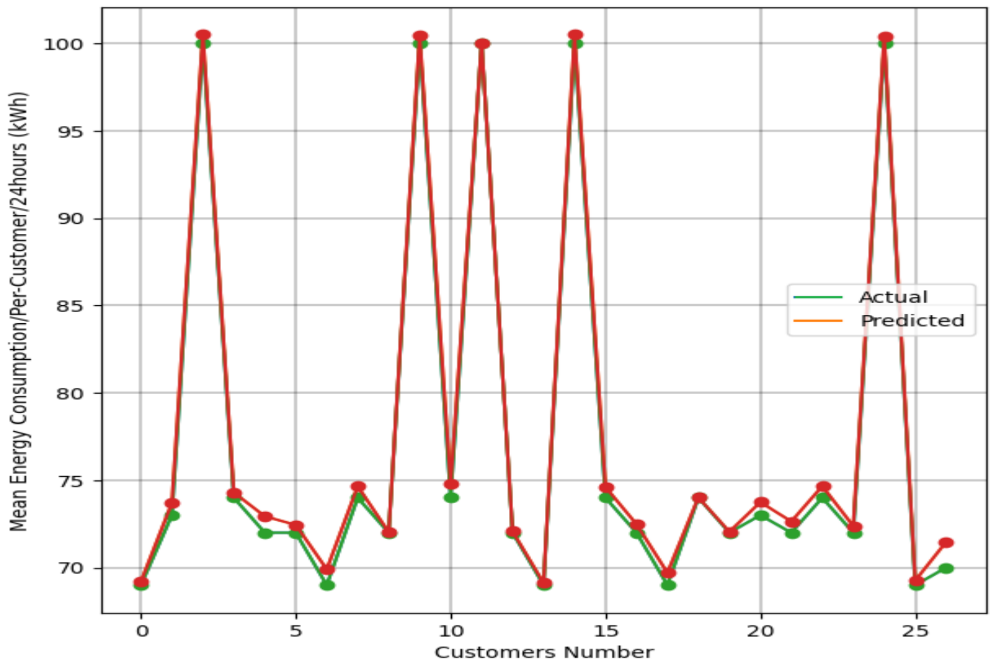



Figure 5-6: Actual and Predicted values curve of the proposed customers

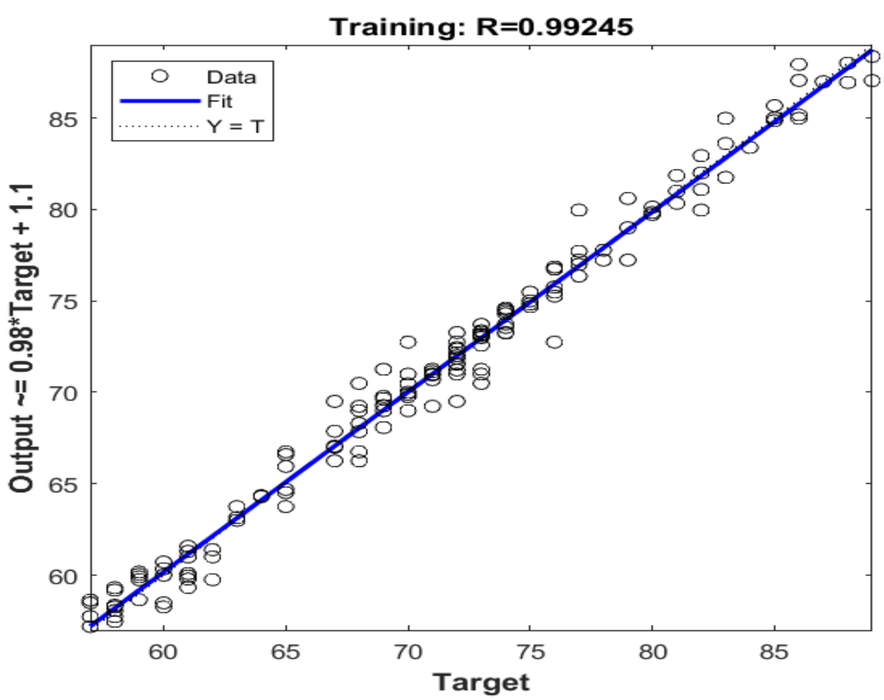



Figure 5-7: Regression plot for DNN

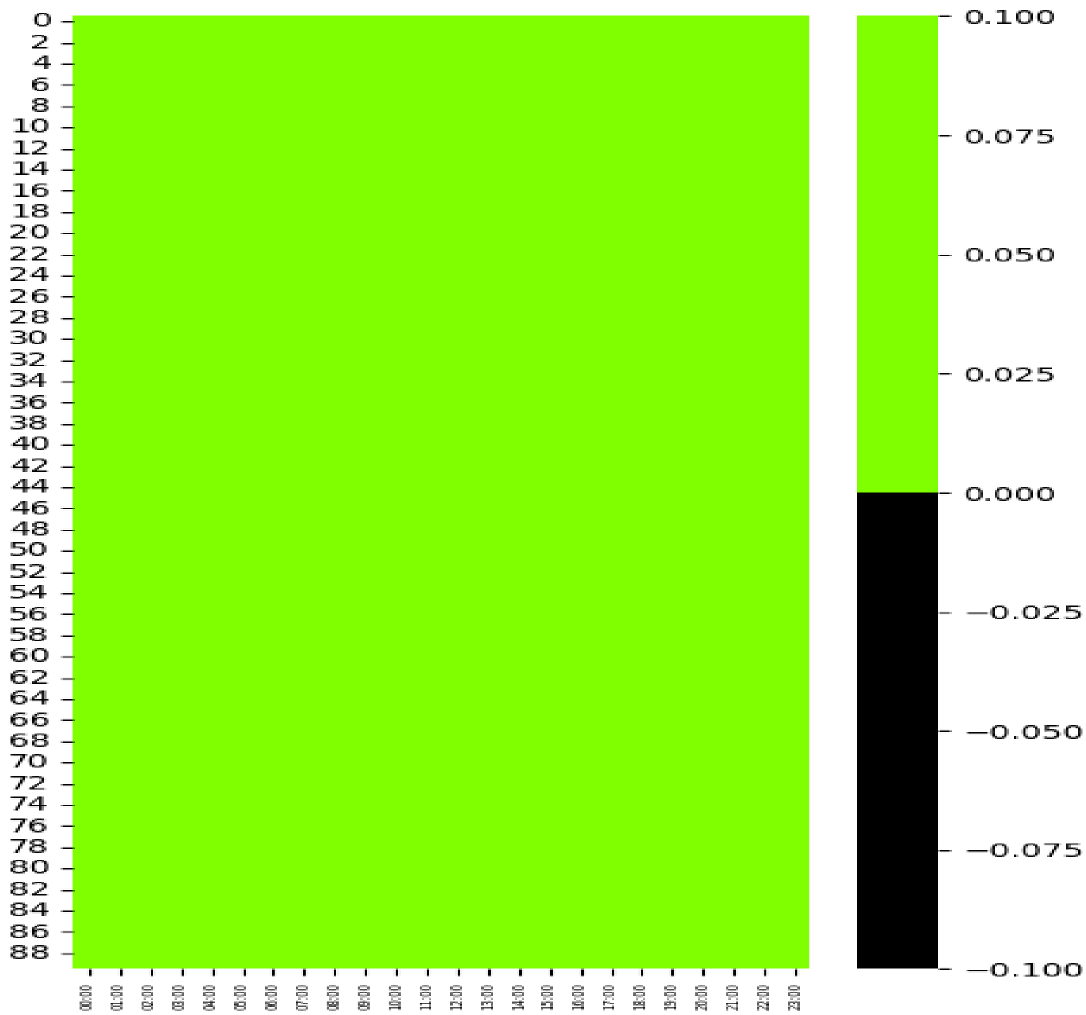



Figure 5-8: Heat-Map relation of the proposed dataset

A heatmap relation of the proposed dataset is showing in Figure 5-8, which is a graphical representation of data in which values in a matrix are represented as colors. It is a way to visualise data in a 2D array and is often used to show the correlation between different variables or to represent data values in a matrix where colors represent different ranges of values. The right side bar clearly shows that the difference between negative and positive values separate at a zero point. Heatmaps are particularly useful when dealing with large datasets, as they can provide a clear visual summary of the data. In Table 5-4, there is the detailed of proposed dataset taken from the results, in which it's feasible to understand the minimum, maximum, mean and various percentages of the consumed energy at customers side during each one hour of the day. In Table 5-5, there is the actual and predicted values, taken from the results, and it's clearly showing that, for a better prediction the predicted values always should be little bit greater than the actual values, however, that extra amount of energy can be stored for other applications like battery storage, vehicle charging stations and various experiments. The details of the dataset is also findable during 24 hours of the day, to find the average, mean, and various percentages of required and consumed energy of generation to demand side.

Table 5-4: Dataset details with energy (kWh) values of proposed customers during 24-hours

| | 00:00 | 01:00 | 02:00 | 03:00 | 04:00 | 05:00 | 06:00 | 07:00 | 08:00 | 09:00 | ... |
|---|---|---|---|---|---|---|---|---|---|---|---|
| count | 90.000000 | 90.000000 | 90.000000 | 90.000000 | 90.000000 | 90.000000 | 90.000000 | 90.000000 | 90.000000 | 90.000000 | ... |
| mean | 70.333333 | 67.422222 | 63.111111 | 62.888889 | 62.777778 | 63.888889 | 67.666667 | 72.444444 | 77.444444 | 73.333333 | ... |
| std | 10.631731 | 13.775061 | 12.492195 | 12.228576 | 11.867980 | 11.182294 | 9.433386 | 7.376109 | 5.365539 | 6.499784 | ... |
| min | 65.000000 | 60.000000 | 56.000000 | 57.000000 | 57.000000 | 58.000000 | 63.000000 | 68.000000 | 73.000000 | 68.000000 | ... |
| 25% | 65.000000 | 61.000000 | 58.000000 | 57.000000 | 58.000000 | 59.000000 | 64.000000 | 69.000000 | 75.000000 | 70.000000 | ... |
| 50% | 67.000000 | 62.000000 | 59.000000 | 58.000000 | 58.000000 | 60.000000 | 64.000000 | 70.000000 | 76.000000 | 72.000000 | ... |
| 75% | 68.000000 | 63.000000 | 60.000000 | 61.000000 | 60.000000 | 62.000000 | 65.000000 | 71.000000 | 77.000000 | 73.000000 | ... |
| max | 100.000000 | 100.000000 | 98.000000 | 97.000000 | 96.000000 | 95.000000 | 94.000000 | 93.000000 | 92.000000 | 91.000000 | ... |

| 14:00 | 15:00 | 16:00 | 17:00 | 18:00 | 19:00 | 20:00 | 21:00 | 22:00 | 23:00 |
|---|---|---|---|---|---|---|---|---|---|
| 90.000000 | 90.000000 | 90.000000 | 90.000000 | 90.000000 | 90.000000 | 90.000000 | 90.000000 | 90.000000 | 90.000000 |
| 70.666667 | 50.288889 | 74.222222 | 75.111111 | 88.000000 | 86.333333 | 82.444444 | 82.888889 | 80.000000 | 75.666667 |
| 9.657040 | 26.619771 | 7.985630 | 7.070185 | 2.172349 | 2.370227 | 3.288082 | 6.507462 | 7.079008 | 8.305948 |
| 64.000000 | 11.000000 | 66.000000 | 68.000000 | 85.000000 | 83.000000 | 79.000000 | 77.000000 | 73.000000 | 68.000000 |
| 65.000000 | 23.000000 | 71.000000 | 72.000000 | 87.000000 | 85.000000 | 81.000000 | 80.000000 | 77.000000 | 72.000000 |
| 68.000000 | 49.500000 | 72.000000 | 73.000000 | 88.000000 | 86.000000 | 82.000000 | 82.000000 | 79.000000 | 74.000000 |
| 69.000000 | 70.750000 | 74.000000 | 75.000000 | 89.000000 | 86.000000 | 83.000000 | 83.000000 | 80.000000 | 75.000000 |
| 97.000000 | 96.000000 | 95.000000 | 94.000000 | 93.000000 | 92.000000 | 91.000000 | 100.000000 | 99.000000 | 98.000000 |

Table 5-5: Actual and Predicted values of proposed customers

| | Actual | Predicted |
|---|---|---|
| 0 | 69 | 69.318058 |
| 1 | 73 | 73.034550 |
| 2 | 100 | 100.234713 |
| 3 | 74 | 74.640419 |
| 4 | 72 | 72.385227 |
| 5 | 72 | 72.494075 |
| 6 | 69 | 69.653785 |
| 7 | 74 | 74.761045 |
| 8 | 72 | 72.604201 |
| 9 | 100 | 100.416567 |
| 10 | 74 | 74.979393 |
| 11 | 100 | 100.897920 |
| 12 | 72 | 72.746242 |
| 13 | 69 | 69.501653 |
| 14 | 100 | 100.250634 |
| 15 | 74 | 74.720893 |
| 16 | 72 | 72.206696 |
| 17 | 69 | 69.287778 |
| 18 | 74 | 74.416841 |
| 19 | 72 | 72.615945 |
| 20 | 73 | 73.540714 |
| 21 | 72 | 72.637961 |
| 22 | 74 | 74.346094 |
| 23 | 72 | 72.546215 |
| 24 | 100 | 100.064407 |
| 25 | 69 | 69.684956 |
| 26 | 70 | 72.078774 |

## 5.4 Energy Prediction having large dataset

If there are large number of customers are integrated with the electrical system, then the energy prediction is more essential to meet and fulfil the required demand of energy for customers. In this dataset there are 1043 customers are integrated into the system, and on the hourly basis there is the energy value of each customer in kWh. The data-head and data-tail of customers are shown in Table 5-6.

Table 5-6: Dataset having 1043 customers

```
[ ] data.head()
```

| | 00:00 | 01:00 | 02:00 | 03:00 | 04:00 | 05:00 | 06:00 | 07:00 | 08:00 | 09:00 | ... | 14:00 | 15:00 | 16:00 | 17:00 | 18:00 | 19:00 | 20:00 | 21:00 | 22:00 | 23:00 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 65 | 62 | 56 | 57 | 58 | 58 | 64 | 70 | 74 | 68 | ... | 64 | 68 | 66 | 68 | 88 | 86 | 80 | 77 | 73 | 68 |
| **1** | 67 | 61 | 57 | 58 | 57 | 59 | 63 | 71 | 75 | 69 | ... | 65 | 68 | 72 | 72 | 87 | 83 | 83 | 77 | 77 | 70 |
| **2** | 65 | 61 | 58 | 57 | 58 | 60 | 63 | 69 | 78 | 70 | ... | 65 | 67 | 68 | 71 | 89 | 86 | 82 | 81 | 77 | 72 |
| **3** | 67 | 63 | 60 | 61 | 60 | 63 | 67 | 70 | 77 | 72 | ... | 67 | 71 | 72 | 73 | 88 | 85 | 81 | 82 | 79 | 75 |
| **4** | 68 | 62 | 60 | 60 | 58 | 62 | 65 | 68 | 76 | 73 | ... | 68 | 70 | 71 | 74 | 87 | 86 | 83 | 82 | 79 | 76 |

5 rows × 24 columns

```
[ ] data.tail()
```

| | 00:00 | 01:00 | 02:00 | 03:00 | 04:00 | 05:00 | 06:00 | 07:00 | 08:00 | 09:00 | ... | 14:00 | 15:00 | 16:00 | 17:00 | 18:00 | 19:00 | 20:00 | 21:00 | 22:00 | 23:00 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1038** | 68 | 62 | 60 | 60 | 58 | 62 | 65 | 68 | 76 | 73 | ... | 68 | 33 | 71 | 74 | 87 | 86 | 83 | 82 | 79 | 76 |
| **1039** | 69 | 62 | 59 | 61 | 61 | 61 | 65 | 71 | 76 | 72 | ... | 72 | 44 | 77 | 75 | 89 | 88 | 82 | 84 | 80 | 75 |
| **1040** | 65 | 100 | 59 | 58 | 58 | 58 | 64 | 69 | 73 | 73 | ... | 69 | 23 | 73 | 76 | 85 | 85 | 79 | 80 | 76 | 73 |
| **1041** | 67 | 61 | 61 | 57 | 59 | 59 | 64 | 71 | 76 | 72 | ... | 69 | 85 | 74 | 73 | 86 | 86 | 81 | 83 | 80 | 74 |
| **1042** | 100 | 99 | 98 | 97 | 96 | 95 | 94 | 93 | 92 | 91 | ... | 97 | 69 | 95 | 94 | 93 | 92 | 91 | 100 | 99 | 98 |

5 rows × 24 columns

By implementing the DNN algorithm as explained in above section, the actual and predicted values are shown in Figure *5-9*, however the difference between the actual and predicted values in overall sum is 68 kWh as shown in Figure *5-10*, which can be used for other applications such as battery storage etc.

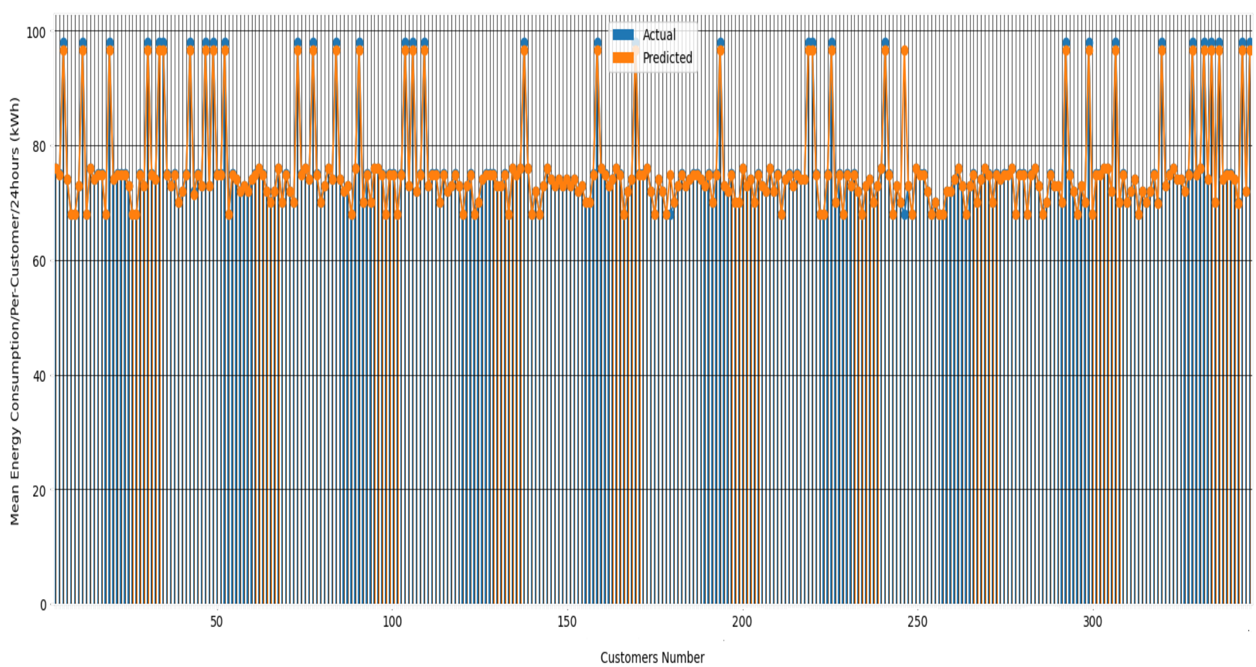



Figure 5-9: Actual and predicted values comparison of each customer per day

```
Actual Values Sum: 518769
Predicted Values Sum: 518837.3164507646
      Actual  Predicted
0         61  61.598963
1         57  59.299711
2         58  58.548127
3         57  58.599078
4         59  60.197926
...      ...        ...
7194      85  85.683635
7195      79  80.331877
7196      80  79.245581
7197      76  75.245581
7198      73  70.878312
```

```
     Actual  Predicted
0        76  76.000000
1        75  74.890726
2        98  96.699550
3        74  74.000000
4        68  68.000000
..      ...        ...
307      74  74.000000
308      70  69.840000
309      98  96.699550
310      72  71.947491
311      98  96.699550
```

Figure 5-10: Actual and predicted values of energy at each customer per day

## 5.5 Feasibility of the Deep Neural Network Algorithm for the Proposed Smart Grid Model

The implementation of Deep Neural Network (DNN) for the proposed model of smart grid, in which there is the consideration of consumers and prosumers energy management. For consumers, there are various aspects discussed in this chapter, in which they can consume required energy with best optimal way. Similarly, for prosumers there are various aspects; by considering they can use their own required energy and also act as a provider and consumer according to energy requirements. Meanwhile, for prosumers those who both consume and produce energy, the feasibility relies on aspects like energy management, grid integration, the regulatory environment, hardware requirements, data sharing, incentives, and grid stability. Ultimately, assessing the feasibility of DNN algorithms in the Smart Grid model entails a careful evaluation of technological, economic, regulatory, and user-centric factors from both consumer and prosumer standpoints.

**The integration of advanced technologies**, particularly Deep Neural Networks (DNNs), into the design and operation of modern Smart Grids has garnered substantial attention due to its potential to revolutionize the energy landscape. As the global demand for electricity grows and the need for efficient energy management becomes increasingly critical, exploring the feasibility of DNN algorithms within the Smart Grid framework is of paramount importance. This inquiry extends beyond the purview of utility companies and grid operators to consider the profound implications and practicality of such implementations from the perspectives of two vital stakeholders: consumers and prosumers.

**Consumers**, as the end-users of energy services, possess unique interests and concerns regarding the integration of DNN algorithms within the Smart Grid. Their primary considerations encompass cost implications, data privacy and security, user-friendliness, energy efficiency, and the adaptability of DNN-driven solutions to their individual preferences and environmental objectives.

**Prosumers**, on the other hand, represent a growing cohort of energy consumers who actively engage in the production and supply of electricity. Their feasibility assessment delves into the optimisation of energy production, seamless grid integration, compliance with evolving regulatory frameworks, the required infrastructure, collaboration opportunities, incentivization mechanisms, and the role DNNs play in enhancing grid stability.

This exploration aims to dissect the multifaceted dimensions of feasibility associated with DNN algorithms in Smart Grid models, emphasizing the pivotal roles consumers and prosumers play in the evolution of energy systems. By scrutinizing the challenges, opportunities, and prerequisites inherent to these two distinct perspectives, we can forge a comprehensive understanding of the feasibility landscape and its implications for the energy ecosystem of the future.

## 5.6 Designing of Neural Network Controller

The first stage of model predictive control is to train a neural network to represent the forward dynamics of the plant (Electrical System). The prediction error between the plant output and the neural network output is used as the neural network training signal. The process is represented by the following Figure 5-11.

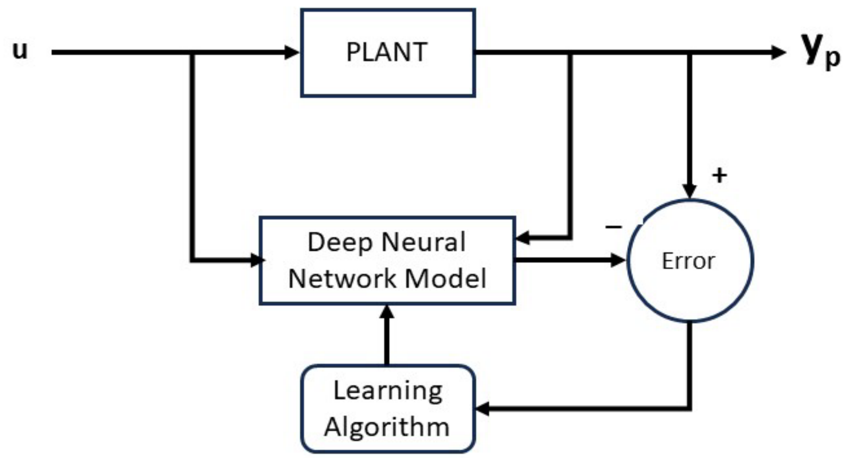



Figure 5-11: Neural Network Controller

The neural network plant model uses previous inputs and previous plant outputs to predict future values of the plant output. The structure of the neural network plant model is given in the following Figure 5-12.

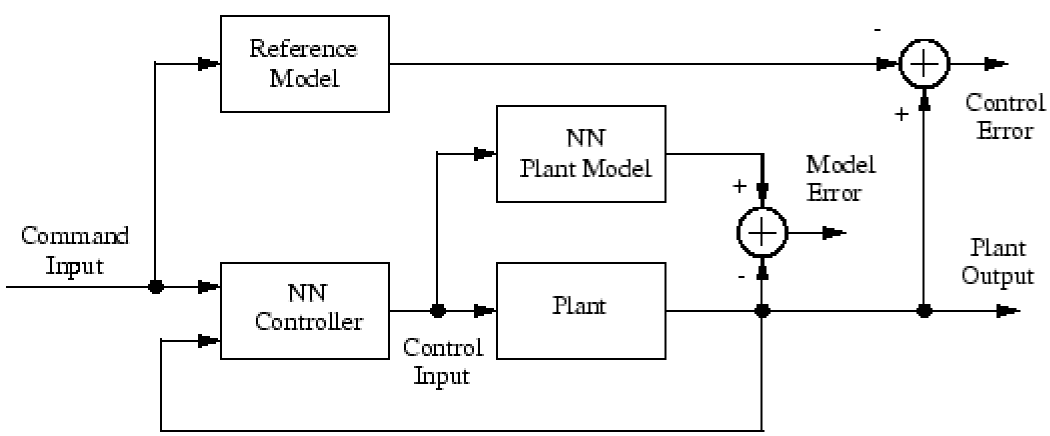



Figure 5-12: The internal mechanism of Neural Network Controller

The model predictive control method is based on the receding horizon technique [SoHa96]. The neural network model predicts the plant response over a specified time horizon. The predictions are used by a numerical optimisation program to determine the control signal that minimizes the following performance criterion over the specified horizon.

$$J = \sum_{j=N_1}^{N_2} (y_r(t+j) - y_m(t+j))^2 + \rho \sum_{j=1}^{N_u} (u'(t+j-1) - u'(t+j-2))^2$$

where $N1$, $N2$, and $Nu$ define the horizons over which the tracking error and the control increments are evaluated. The $u'$ variable is the tentative control signal, $yr$ is the desired response, and $ym$ is the network model response. The ρ value determines the contribution that the sum of the squares of the control increments has on the performance index.

The Figure 5-13, illustrates the model predictive control process. The controller consists of the neural network plant model and the optimisation block. The optimisation block determines the values of $u'$ that minimize $J$, and then the optimal $u$ is input to the plant. The controller block is implemented in Simulink, as described in the following section.

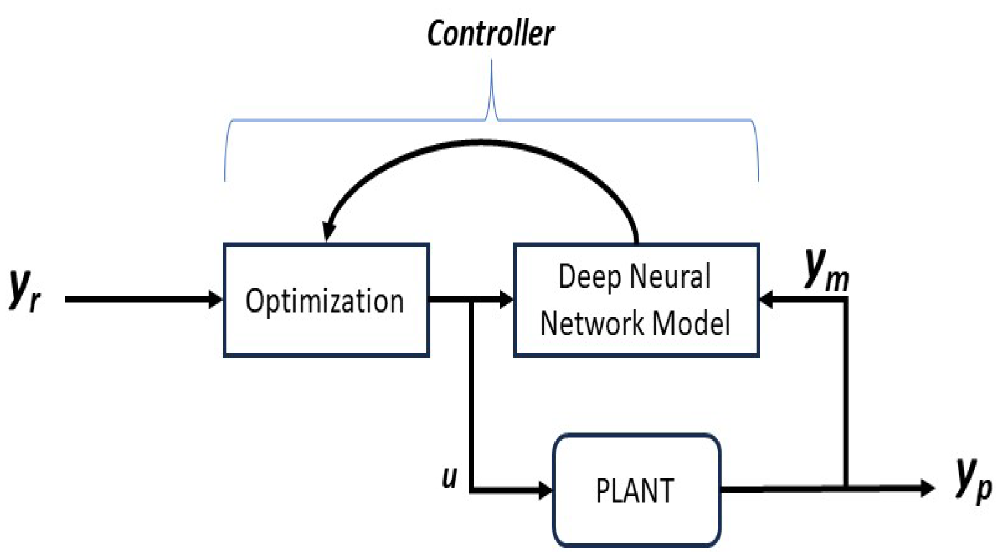



Figure 5-13: Process of Neural Network Controller to Optimise the system

## 5.7 Proposed Model for Implementation

In Figure 5-14, show the proposed model of electrical system for energy management, in which 9-customers are integrated with the power grid having input of 6000 volts. Battery storage and solar energy source is also integrated with the system for the backup of electrical energy.

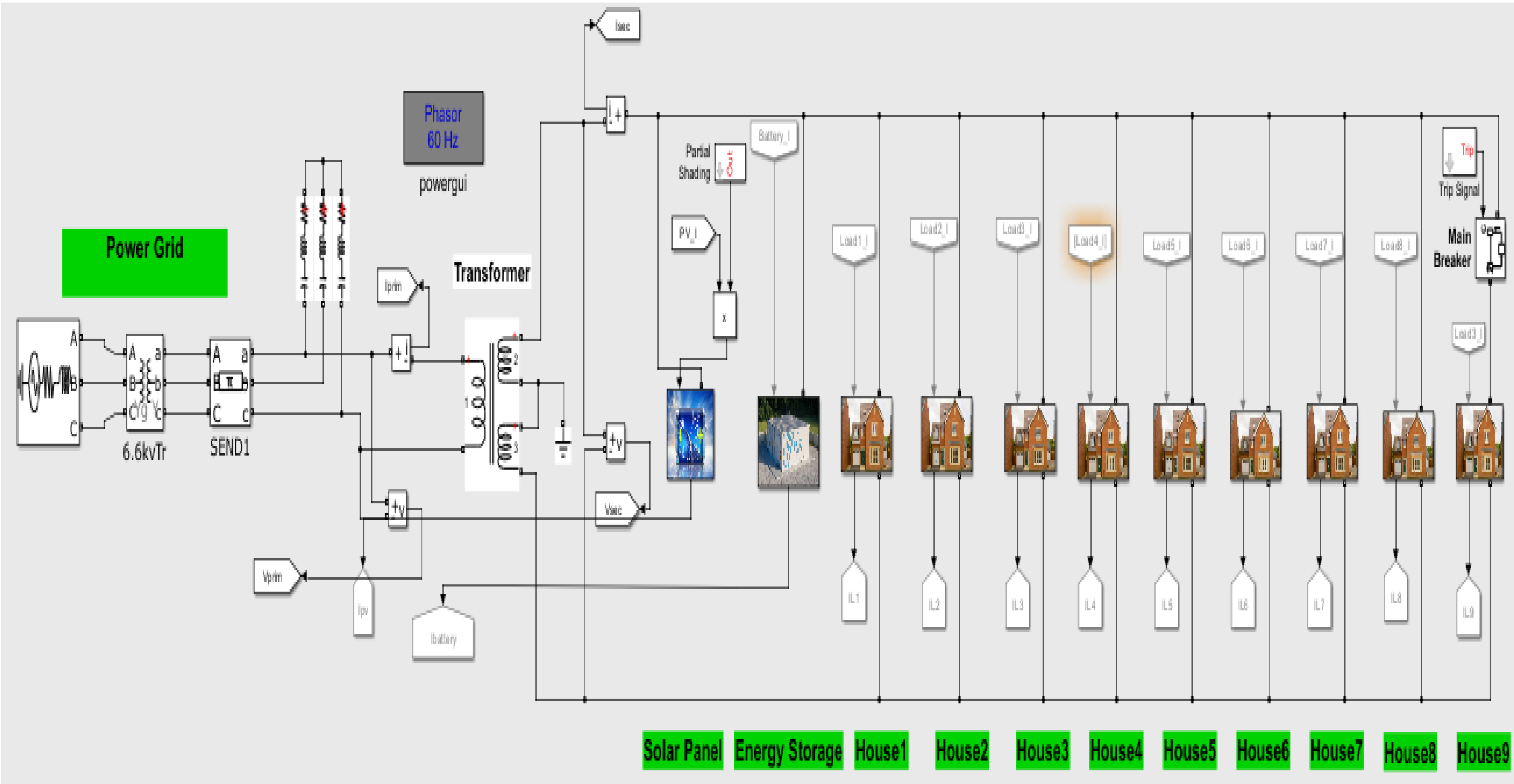



Figure 5-14: The proposed Electrical Model for energy management Implementations

In Figure 5-15, there is an internal structure of the model to sum-up the energy of all customers, and then separate it through active and reactive power blocks to showing it as a separate source or consumption block at the output. In Figure 5-16, the battery storage and neural network controller blocks are also integrated with the proposed electrical system, for the better usage of battery storage and the implementation of neural network controller to optimise the overall electrical system.

In Figure 5-17, there is the running time of the model, which is 86400 seconds, and 24-hours of the day, these seconds are divided into 24 parts for the better understanding of power consumption during each hour of the day. There are various plots are showing in comparison perspective, In which it's showing that when the maximum power is generated from PV system, then the mostly power is stored in battery and use for load, however during that time the power from the secondary source is minimum. SOC, or State of Charge, is a metric that represents the remaining capacity or charge level of a battery, typically expressed as a percentage. It indicates how much energy is left in the battery relative to its full capacity. For instance, a SOC of 100% means the battery is fully charged, while a SOC of 0% indicates it is completely discharged.

SOC can be estimated through methods such as discharge tests, which involve measuring how much charge the battery can deliver under controlled conditions. Monitoring SOC is essential for efficient battery management, as it helps optimise when to charge or discharge the battery to match energy needs, particularly in systems using renewable sources like photovoltaic (PV) systems. Accurate SOC tracking supports smart grid applications and zero-energy building concepts, as it allows prosumers to better manage their energy usage and generation.

The SOC of a battery, that is, its remaining capacity, can be determined using a discharge test under controlled conditions, and SOC curve is showing that the battery usage is maximum when there is battery storage from PV systems or other renewable sources. In this way, it's possible to meet the concept of zero-energy building, when all required demand of power will be equal to energy generated from renewable sources. In this research just a PV system is used, however other sources of renewable can be integrated with the system for minimum usage of grid power. In this way in terms of consumers and prosumers can adjust the power usage and generation by using their own renewable energy.

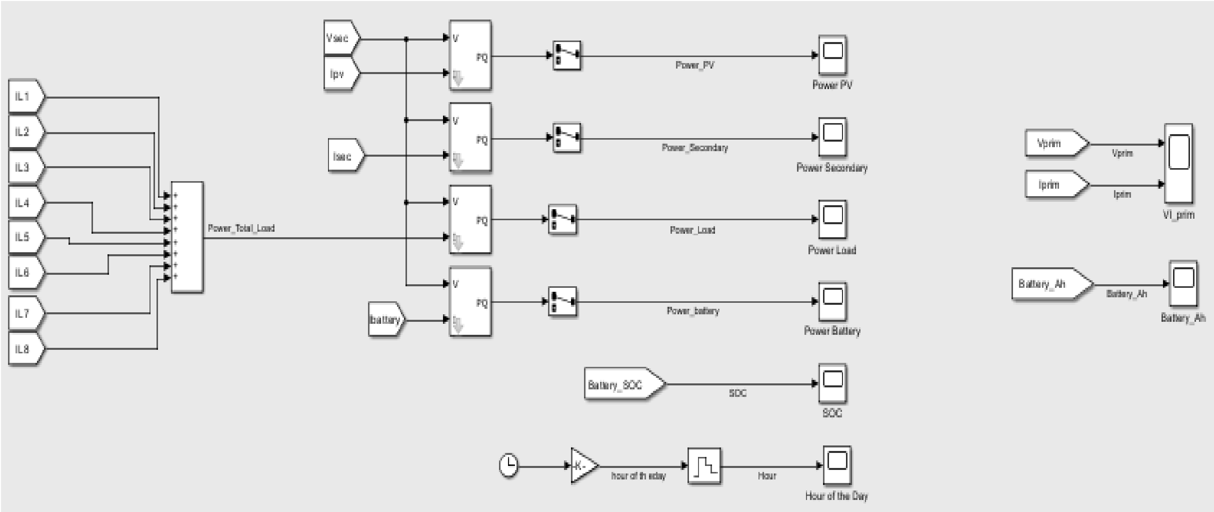



Figure 5-15: Internal structure for the management of energy

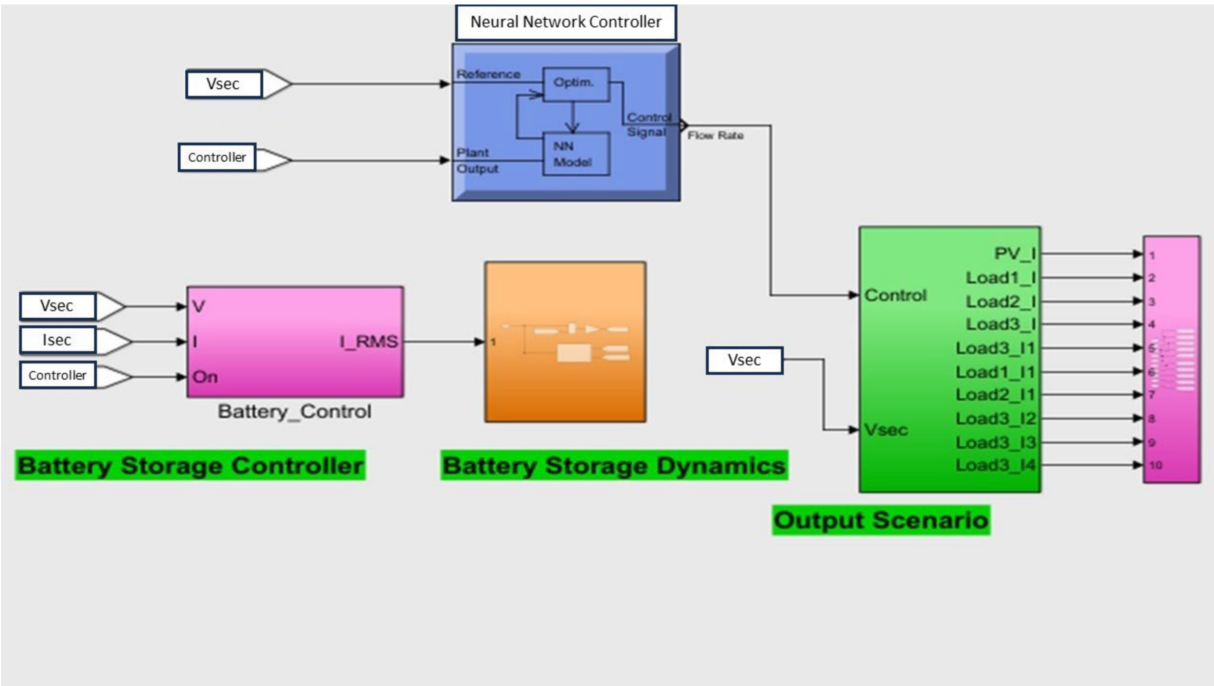



Figure 5-16: Battery Storage and Neural Network Controllers

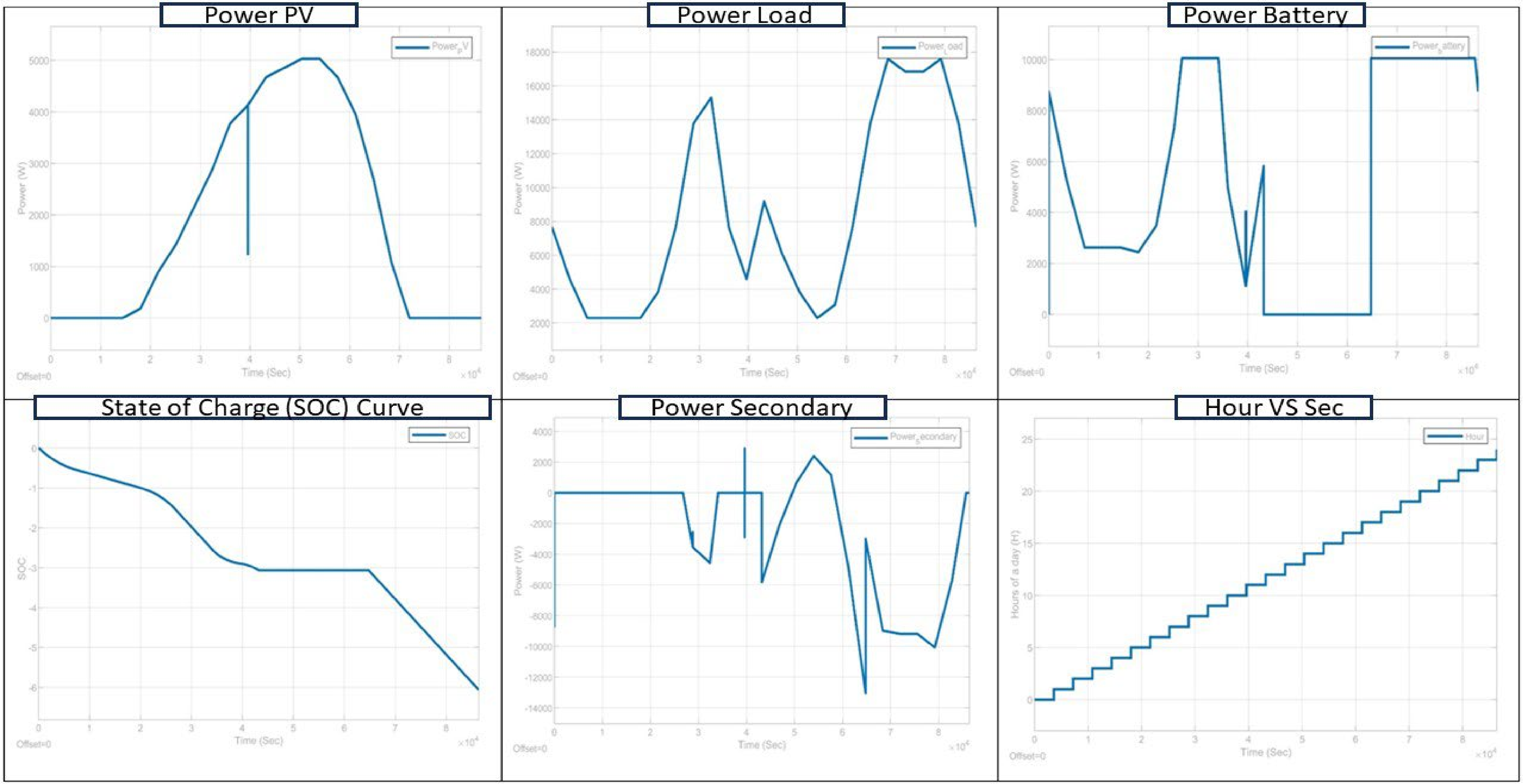



Figure 5-17**:** Overview of Model results as comparison of each state (PV, Secondary Source, Battery Storage, SOC, Load-Side)

## 5.8 Smart Grid Energy Management Towards Net Zero

The modern evaluation of smart grid evolves the integration of renewable energy sources both at grid and customer side. Customer involves both consumer and prosumer for consume and produce energy. This dynamic environment of smart grid needs fast and efficient system to optimise the energy balance and efficiency and achieving sustainability goals when large number of consumers and prosumers are integrated with the system. In this section, there is a design and implementation of a deep neural network (DNN)-based optimisation framework for clustered demand-side energy management in smart grids. The framework involves clustering customers based on their energy consumption and production patterns and applying DNNs to predict and optimise energy usage to achieve a net-zero balance.

### 5.8.1 Overview of the Proposed System

The proposed system is designed for energy management of consumers and prosumers and optimisation of smart grid by implementing the novel technique of deep neural network. The proposed architecture of implementation consists of the following steps.

- **Data Collection:** Collection of energy data for both consumers and prosumers.
- **Preprocessing**: Prepare the data for both consumers and prosumers. For prosumers there is a need to collect the data for both consumptions and production.
- **Clustering**: Implementation of K-Means clustering by elbow method to generate the clusters for both consumers and prosumers.
- **Prediction**: Implementing a DNN to predict energy consumption and production for each cluster.
- **Net-Zero Energy**: Adjusting energy production and consumption to achieve a net-zero energy balance.

This process will operate continuously on a real time data for a specific time interval of 30 minutes for prediction and optimisation of the overall system. The general flow chart of implementation is showing in Figure 5-18.

### 5.8.2 Data Flow and Interaction Between Components

Central database in the smart grid will store and process the data, which will be collected from the smart meter and installed at the clusters hub for consumer and prosumer premises. This data contains timestamps, energy consumed by each consumer, and energy produce and consumer by each prosumer. After preprocessing, the data is fed into the clustering module, which segments customers into distinct clusters. These clusters are then used as input for the DNN, which predicts future energy needs. The predicted data is utilized by the optimisation module to adjust the energy flow, ensuring that the system moves towards a net-zero energy balance. The overall flowchart for the implementation of data is showing in Figure 5-18.

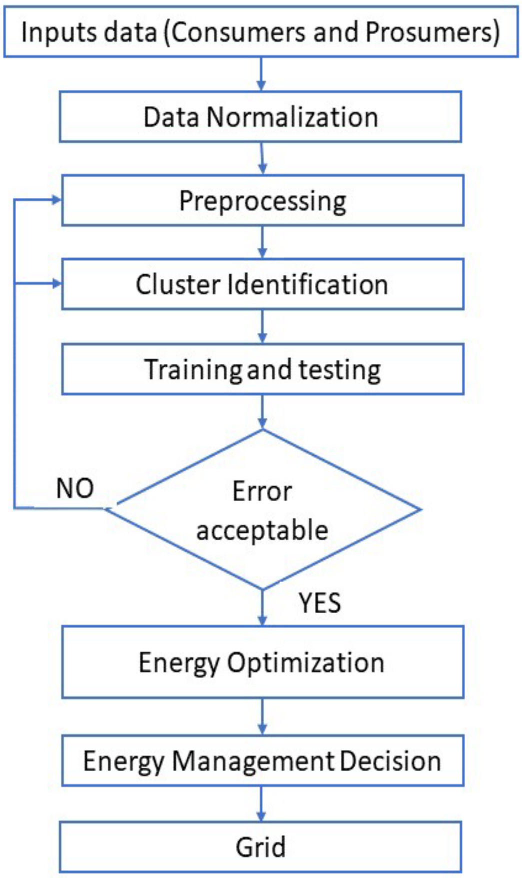



Figure 5-18: Flow chart to implement the data for energy optimisation

## 5.9 Data Collection and Preprocessing

### 5.9.1 Smart Meters and IoT Devices

Smart meters and Internet of Things (IoT) devices serve as the main sources of data in smart grids and are installed at consumer and prosumer premises to measure and record various parameters, such as electricity consumption, generation, voltage, current, and power quality. The intervals at which smart meters read electricity consumption data can vary, ranging from a few seconds to every 30 minutes, depending on the configuration and requirements of the smart grid system.

- Consumers: These entities are traditional energy users who consume electricity.
- Prosumers: These entities typically utilise both electricity consumption and production, frequently employing renewable sources such as solar panels.

### 5.9.2 Data Acquisition and Communication

The smart meters and IoT devices gather data that is transmitted to the central system for processing. This can be done through a range of communication technologies:

- Wireless Communication: Wi-Fi, Zigbee, LoRaWAN, and cellular networks (4G/5G).
- Wired Communication: Power Line Communication (PLC) and fiber optics.

### 5.9.3 Data Aggregation and Preprocessing

Once the data is collected and delivered to the central system, it must be compiled and pre-processed, a process that entail:

- Data Cleaning: Removing any corrupt or erroneous data points.
- Data Aggregation: The process of condensing information while preserving the vital aspects.
- Timestamp Synchronization: To temporal analysis, making sure that every data point is precisely timestamped.

### 5.9.4 Real-Time Data Storage and Management

The processed data is kept in databases made to manage substantial amounts of data that are updated in real time. Typical options include:

- Time-Series Databases: InfluxDB, OpenTSDB, and TimescaleDB.
- Distributed Storage Systems: Hadoop HDFS, Apache Cassandra, and Amazon S3.

### 5.9.5 Data Analysis and Visualization

To get insights and support decision-making, the gathered data is analysed. This may include:

- Real-Time Monitoring: Dashboards showing the generation trends, consumption patterns, and current grid status.
- Predictive Analytics: Predicting demand, spotting irregularities, and streamlining grid operations via machine learning algorithms.

As per the released study by the UK's Department of BEIS,

| |
|---|
| • https://www.gov.uk/government/statistics/energy-consumption-in-the-uk-2022 |
| • https://ukpowernetworks.opendatasoft.com/explore/dataset/grid-and-primary-sites/information/ |
| • Data View (entsoe.eu) |

The average energy use in kWh for every 30-minute interval in the United Kingdom

- ➢ **Small Houses**
- **Average Usage**: The usual hourly energy consumption of small residences in the UK ranges from 1.2 to 2.5 kWh.
- **Per 30-Minutes**: This corresponds to between 0.6 and 1.25 kWh per thirty minutes.
- ➢ **Large Houses**
- **Average Usage**: The average energy usage of large residences in the UK is greater, ranging from 2.5 to 5 kWh per hour.
- **Per 30-Minutes**: This corresponds to between 1.25 and 2.5 kWh per thirty minutes.

### 5.9.6 Steps for Code Implementation

The main steps of how's the code imports, define and runs are the following:

| |
|---|
| START |
| **1. IMPORTS AND INITIALIZATION:** |
| - Import necessary libraries: |
| - pandas for data manipulation |
| - numpy for numerical operations |

| |
|---|
| - datetime and timedelta for date/time handling |
| **2. DEFINE PARAMETERS:** |
| - num_customers = total number of customers |
| - num_prosumers = number of prosumers (consume and produce energy) |
| - num_consumers = number of consumers (only consume energy) |
| - interval_minutes = 30 (time interval for data collection) |
| - total_intervals = 24 hours / interval_minutes = 48 (number of intervals in a day) |
| 3. GENERATE TIME INTERVALS FOR ONE DAY: |
| - start_time = January 1, 2024 |
| - time_intervals = generate a list of timestamps at 30-minute intervals for the 24-hour period |
| **4. CREATE CUSTOMER IDS AND TYPES:** |
| - customer_ids = generate unique IDs for each customer |
| - types = create a list of customer types (prosumer or consumer) |
| - Randomly shuffle the customer types to assign each customer as either prosumer or consumer |
| **5. GENERATE DATA:** |
| - Initialize an empty list called data to store generated data |
| - FOR each time_interval in time_intervals: |
| - FOR each customer in customer_ids: |
| - IF customer is prosumer: |
| - consumption_kwh = randomly generate a value between 0.5 and 3.0 kWh |
| - production_kwh = randomly generate a value between 0.0 and 2.0 kWh |
| - ELSE (customer is consumer): |
| - consumption_kwh = randomly generate a value between 0.5 and 3.0 kWh |
| - production_kwh = 0.0 kWh |
| |
| - Append a new data point to the data list: |
| - [timestamp, customer_id, customer_type, consumption_kwh, production_kwh] |

| **6. CREATE DATA FRAME AND SAVE TO CSV:** |
|---|
| - Convert the data list into a pandas DataFrame |
| - Assign appropriate column names: ['timestamp', 'customer_id', 'customer_type', 'consumption_kwh', 'production_kwh'] |
| - Save the DataFrame to a CSV file named 'energy_consumption_data.csv' |
| - Print confirmation message with file path |
| **7. SMART GRID SIMULATION CONTEXT:** |
| - Simulate the role of IoT devices and smart meters in tracking energy consumption and production |
| - Data is collected at 30-minute intervals, reflecting real-time smart grid operations |
| - The centralized DataFrame represents aggregated data for further monitoring and analysis |
| - The CSV file acts as a storage medium for smart grid energy management and optimisation processes |
| END |

The implemented code simulates the data collection of energy consumption and production for consumers and prosumers in a smart grid over a 24-hour period, with data points recorded every 30 minutes. The small portion of proposed dataset is showing in Table 5-7, which showing the 20 values of customers, including consumers and prosumers, and in Table 5-8, is showing the data-head and data tail of the overall proposed data.

Table 5-7: Proposed data for implementation

| 1 | timestamp | customer_ type | | consumption_kwh | production_kwh | energy_source | category |
|---|---|---|---|---|---|---|---|
| 2 | 01/01/2024 00:00 | 1 | consumer | 1.370889205 | 0 | N/A | home |
| 3 | 01/01/2024 00:00 | 2 | consumer | 0.219584185 | 0 | N/A | home |
| 4 | 01/01/2024 00:00 | 3 | consumer | 1.005899829 | 0 | N/A | home |
| 5 | 01/01/2024 00:00 | 4 | high_demand_consumer | 2.50100596 | 0 | N/A | industrial |
| 6 | 01/01/2024 00:00 | 5 | consumer | 0.534697539 | 0 | N/A | home |
| 7 | 01/01/2024 00:00 | 6 | consumer | 0.672257831 | 0 | N/A | home |
| 8 | 01/01/2024 00:00 | 7 | consumer | 1.451302236 | 0 | N/A | home |
| 9 | 01/01/2024 00:00 | 8 | prosumer | 0.660364424 | 1.474851646 | wind | home |
| 10 | 01/01/2024 00:00 | 9 | consumer | 1.224146864 | 0 | N/A | home |
| 11 | 01/01/2024 00:00 | 10 | consumer | 1.261656406 | 0 | N/A | home |
| 12 | 01/01/2024 00:00 | 11 | high_demand_consumer | 1.864541355 | 0 | N/A | office |
| 13 | 01/01/2024 00:00 | 12 | consumer | 0.340144187 | 0 | N/A | home |
| 14 | 01/01/2024 00:00 | 13 | consumer | 0.825732373 | 0 | N/A | home |
| 15 | 01/01/2024 00:00 | 14 | consumer | 0.846833336 | 0 | N/A | home |
| 16 | 01/01/2024 00:00 | 15 | consumer | 1.328337273 | 0 | N/A | home |
| 17 | 01/01/2024 00:00 | 16 | consumer | 1.095679378 | 0 | N/A | home |
| 18 | 01/01/2024 00:00 | 17 | prosumer | 1.203930319 | 0.486699538 | solar | home |
| 19 | 01/01/2024 00:00 | 18 | consumer | 0.888021925 | 0 | N/A | home |
| 20 | 01/01/2024 00:00 | 19 | consumer | 1.288291571 | 0 | N/A | home |

Table 5-8: Data-head and data-tail of the main data

```
Data Head (First 5 Rows):
             timestamp  customer_id  energy_consumed  is_prosumer  \
0  2022-01-01 00:00:00            1         1.652050            0
1  2022-01-01 00:30:00            1         1.853666            0
2  2022-01-01 01:00:00            1         2.209337            0
3  2022-01-01 01:30:00            1         2.593140            0
4  2022-01-01 02:00:00            1         1.101900            0

  prosumer_type  energy_produced  net_consumption
0           NaN              0.0         1.652050
1           NaN              0.0         1.853666
2           NaN              0.0         2.209337
3           NaN              0.0         2.593140
4           NaN              0.0         1.101900

Data Tail (Last 5 Rows):
                  timestamp  customer_id  energy_consumed  is_prosumer  \
479995  2022-01-01 21:30:00        10000         2.888672            0
479996  2022-01-01 22:00:00        10000         0.649552            0
479997  2022-01-01 22:30:00        10000         2.348183            0
479998  2022-01-01 23:00:00        10000         0.745230            0
479999  2022-01-01 23:30:00        10000         1.113037            0

       prosumer_type  energy_produced  net_consumption
479995           NaN              0.0         2.888672
479996           NaN              0.0         0.649552
479997           NaN              0.0         2.348183
479998           NaN              0.0         0.745230
479999           NaN              0.0         1.113037
```

### 5.9.7 Synthetic Data Generation

To replicate the energy consumption and production patterns of customers, synthetic data was created due to the difficulties in obtaining large-scale real-world data. Prosumers, who produce their own energy from renewable sources like solar and wind, were included in the dataset design. A thorough dataset for testing the framework was produced by recording each customer's data for a whole day at a resolution of thirty-minute intervals.

### 5.9.8 Feature Extraction and Scaling

Essential elements including energy production, consumption, net energy balance, and hourly usage patterns were extracted from the raw data. Z-score normalisation was used to standardise these features to guarantee the efficient operation of the clustering and prediction models. Scaling is a necessary step in machine learning algorithms' convergence since it changes the features' mean and standard deviation to zero and one, respectively.

## 5.10 Customer Clustering

### 5.10.1 Introduction to Clustering in Energy Data Analysis

Clustering is a critical unsupervised machine learning technique that groups data points based on their intrinsic characteristics without prior labels. In energy data analysis, clustering can uncover hidden patterns in customer behaviour, such as how different groups of customers consume and produce energy. This approach is particularly valuable for utilities and policymakers aiming to design tailored energy management strategies.

This study employs the K-Means clustering algorithm on a synthetic dataset of energy consumption and production. The dataset includes both consumers (who only consume energy) and prosumers (who both consume and produce energy) over a 24-hour period, with data recorded at 30-minute intervals. The goal is to segment these customers into distinct clusters based on their energy behaviours, which can inform more effective energy management practices.

### 5.10.2 Dataset Preparation and Feature Engineering

The dataset contains energy consumption data for 10,000 customers, with 15% identified as prosumers. For clustering, key features were selected, including energy consumption, energy production, net energy consumption (difference between consumed and produced energy), the hour of the day, and the day of the week. These features are crucial for capturing temporal patterns and the dynamic behavior of energy use and generation.

**Feature Selection**:

| |
|---|
| • **Energy Consumed (energy_consumed)**: The total amount of energy consumed by a customer at each time interval. |
| • **Energy Produced (energy_produced)**: The amount of energy produced by prosumers. |
| • **Net Consumption (net_consumption)**: Calculated as energy_consumed - energy_produced, indicating whether a customer is a net consumer or producer of energy at any given time. |
| • **Hour (hour)**: The hour of the day, capturing daily energy consumption and production cycles. |
| • **Day of the Week (day_of_week)**: Captures potential weekly patterns in energy use. |

**Normalization**: To ensure that each feature contributes equally to the clustering process, the features are standardized using Standard-Scaler. This step is essential as it prevents features with larger ranges (e.g., energy values) from dominating the clustering process.

### 5.10.3 Determining the Optimal Number of Clusters Using the Elbow Method

**Elbow Method**: The elbow method is employed to determine the optimal number of clusters (k). The method involves plotting the within-cluster sum of squares (WCSS) for different values of k and identifying the "elbow" point where the reduction in WCSS begins to taper off. This point represents the most appropriate number of clusters, balancing simplicity with the ability to capture the structure in the data.

In this study, the elbow was observed at $k=3$, indicating that three clusters provide a meaningful segmentation of the customer base without overfitting.

### 5.10.4 Application of K-Means Clustering

**K-Means Clustering**: With $k=3$ as the determined optimal number of clusters, the K-Means algorithm is applied. This algorithm partitions the customers into three distinct clusters, each characterised by a centroid that represents the average behavior of customers within that cluster. The algorithm iteratively adjusts these centroids to minimize the distance between customers and their assigned centroids.

**Cluster Analysis**: The clusters are analysed to understand their composition and characteristics. This involves examining the mean values of key features within each cluster and determining the number of consumers and prosumers in each cluster.

- **Cluster 0**: This cluster may predominantly include consumers with lower or steady energy consumption and minimal or no energy production.
- **Cluster 1**: Likely to contain prosumers with significant energy production, particularly during daylight hours (e.g., solar energy producers).
- **Cluster 2**: A mix of consumers and prosumers, potentially including those with more complex energy management strategies, such as battery storage.

### 5.10.5 Visualization of Cluster Results

**Scatter Plots**: Scatter plots provide a visual representation of the clustering results, highlighting how different clusters behave in terms of energy consumption and production.

- **Hourly Net Consumption**: Visualises how net consumption varies throughout the day for each cluster.
- **Energy Consumption vs. Production**: Shows the relationship between energy consumed and produced, helping to differentiate between consumers and prosumers within each cluster.

**Bar and Pie Charts**: To clearly represent the distribution of consumers and prosumers within each cluster:

- **Bar Charts**: Show the absolute number of consumers and prosumers in each cluster, providing a straightforward comparison.
- **Pie Charts**: Illustrate the relative proportions of consumers and prosumers within each cluster, offering an intuitive understanding of cluster composition.

### 5.10.6 Methodology and Implementation

**Step-by-Step Implementation**:

1. **Data Loading and Preprocessing**: Load the dataset, engineer features, and standardize them for clustering.
2. **Optimal Cluster Determination**: Use the elbow method to identify the optimal number of clusters (k=3).
3. **K-Means Clustering**: Apply K-Means to segment customers into clusters based on their energy behaviors.
4. **Cluster Analysis**: Analyse the composition of each cluster, including the distribution of consumers and prosumers.
5. **Visualization**: Generate scatter plots, bar charts, and pie charts to visualise and interpret the clustering results.

- **K**: Range of potential cluster numbers, from 1 to 10.
- **WCSS**: Within-Cluster Sum of Squares is calculated for each value of k.
- **Red Highlight**: The point corresponding to k=3 is highlighted in red to show that this is the optimal number of clusters.

This graph will clearly show the Elbow point at k=3.

The Elbow Method is used to determine the best number of clusters, represented by the "elbow" in the plot. In this case, 3 clusters (k=3) is selected as the optimal number as shown in Figure 5-19. This balances complexity with the ability to distinguish consumer-prosumer behaviour.

Using K-Means clustering, customers are grouped into 3 distinct clusters. By including is prosumer in the features, the algorithm considers whether a customer is a prosumer or consumer, resulting in a mix within each cluster. The percentage of consumer and prosumer in each cluster is showing in Figure 5-20. However the deviation od consumer and prosumer in each cluster is showing in Figure 5-21 and Figure 5-22, which shows that in cluster-0, there are 1448 prosumers and in cluster-1 there are 4304 consumers and similarly in cluster-2 there are 4248 consumers.

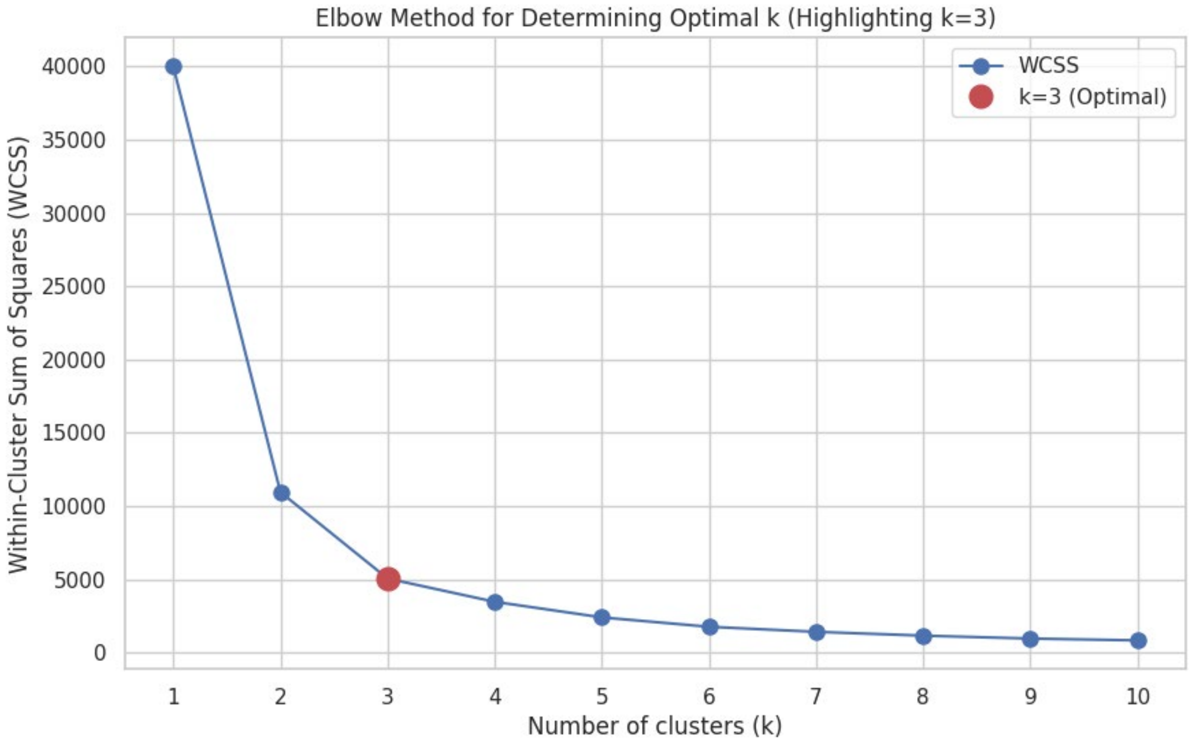



Figure 5-19: Elbow method to determine the optimal cluster number

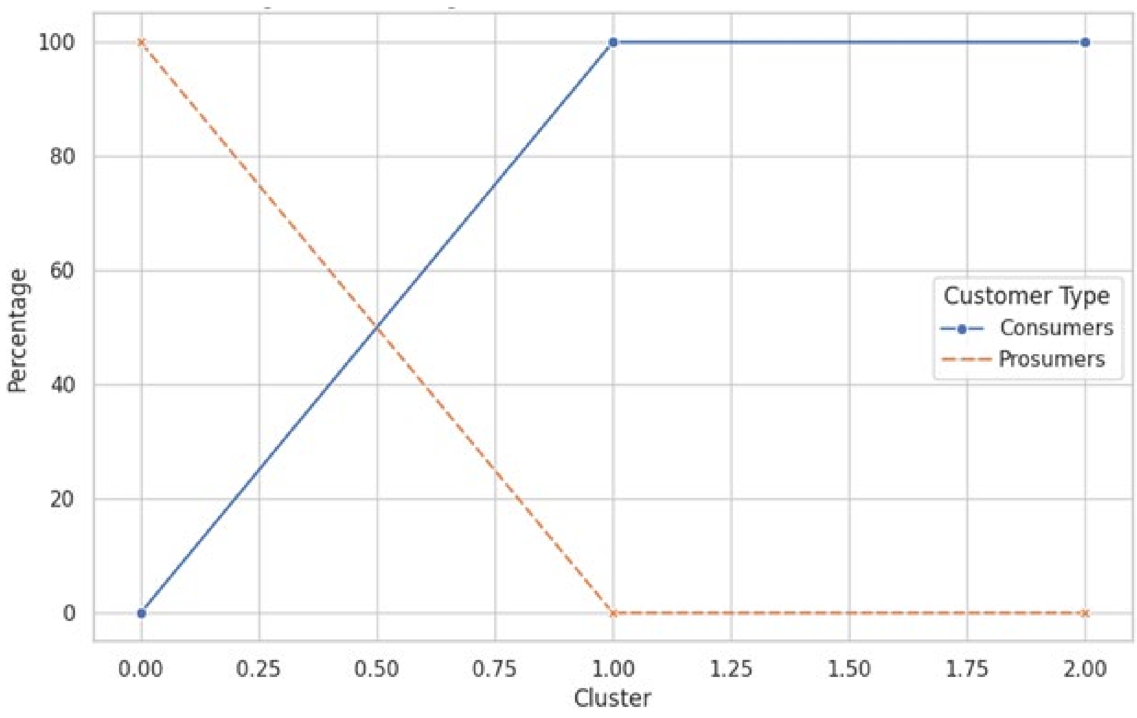



Figure 5-20: Percentage of consumers and prosumers in each cluster

Figure 5-21: Number of customers in each cluster shows the number of consumers and prosumers in each cluster. The average energy consumption and production in each cluster is showing in Figure 5-23 and Figure 5-24, which shows that there is a consumption of energy in each cluster but the production of energy is just in cluster-0.

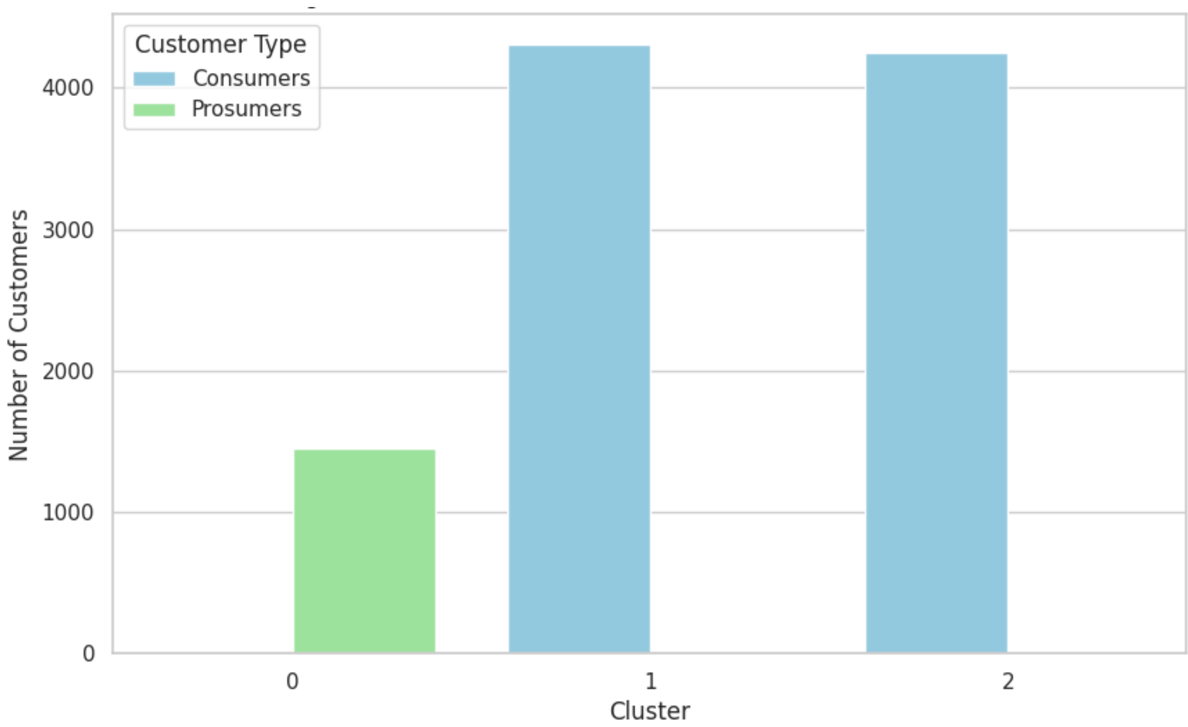



Figure 5-21: Number of customers in each cluster

```
Division of Consumers and Prosumers in Each Cluster:
         Consumers  Prosumers  Total_Customers
cluster
0                0       1448             1448
1             4304          0             4304
2             4248          0             4248
```

Figure 5-22: Division of consumers and prosumers in each cluster

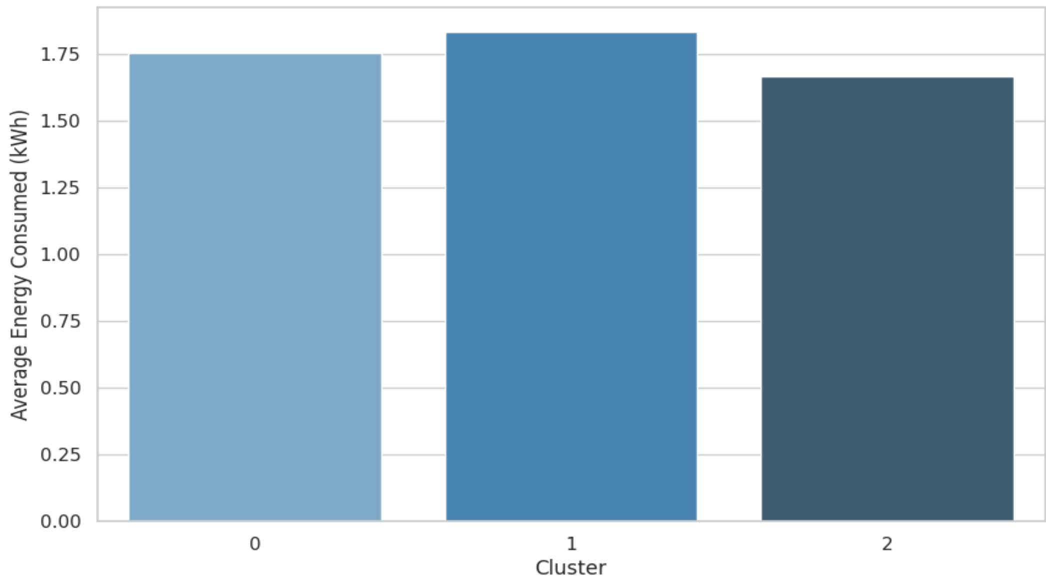



Figure 5-23: Average energy consumption in each cluster

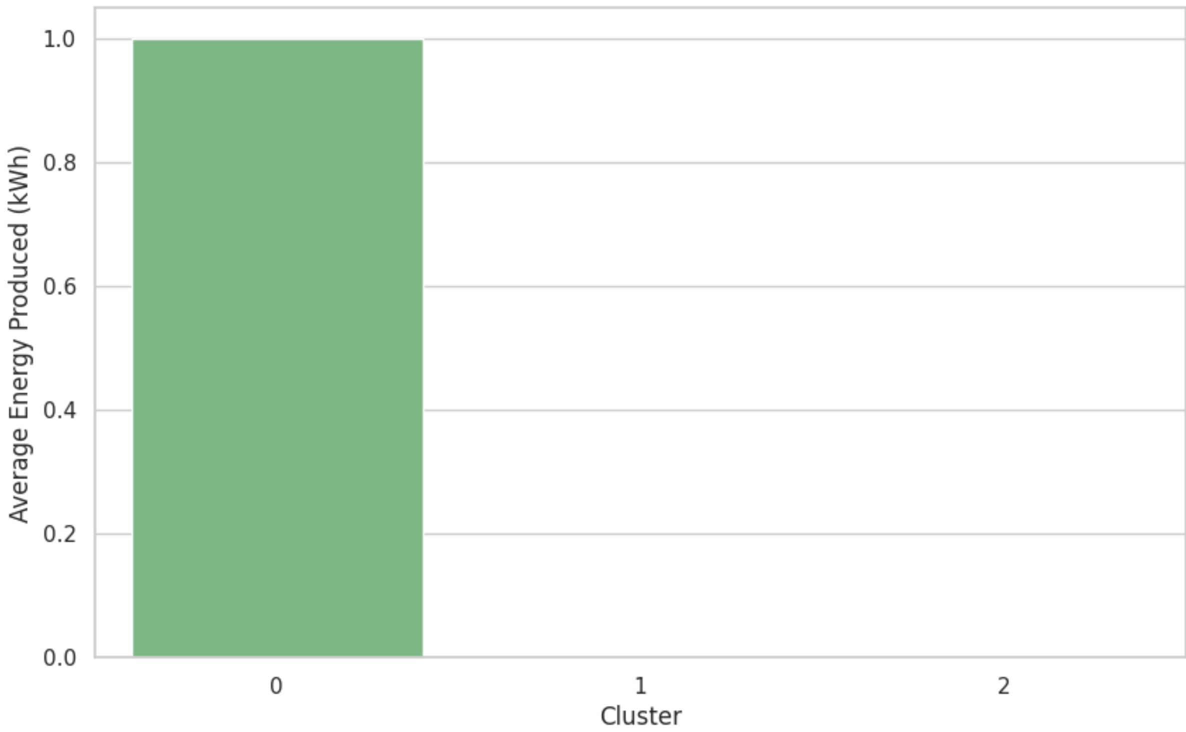



Figure 5-24: Average energy production in each cluster

Figure 5-25 provides a correlation heatmap, which shows how different features (e.g., energy consumption, production, hour of the day, and whether a customer is a prosumer) relate to one another.

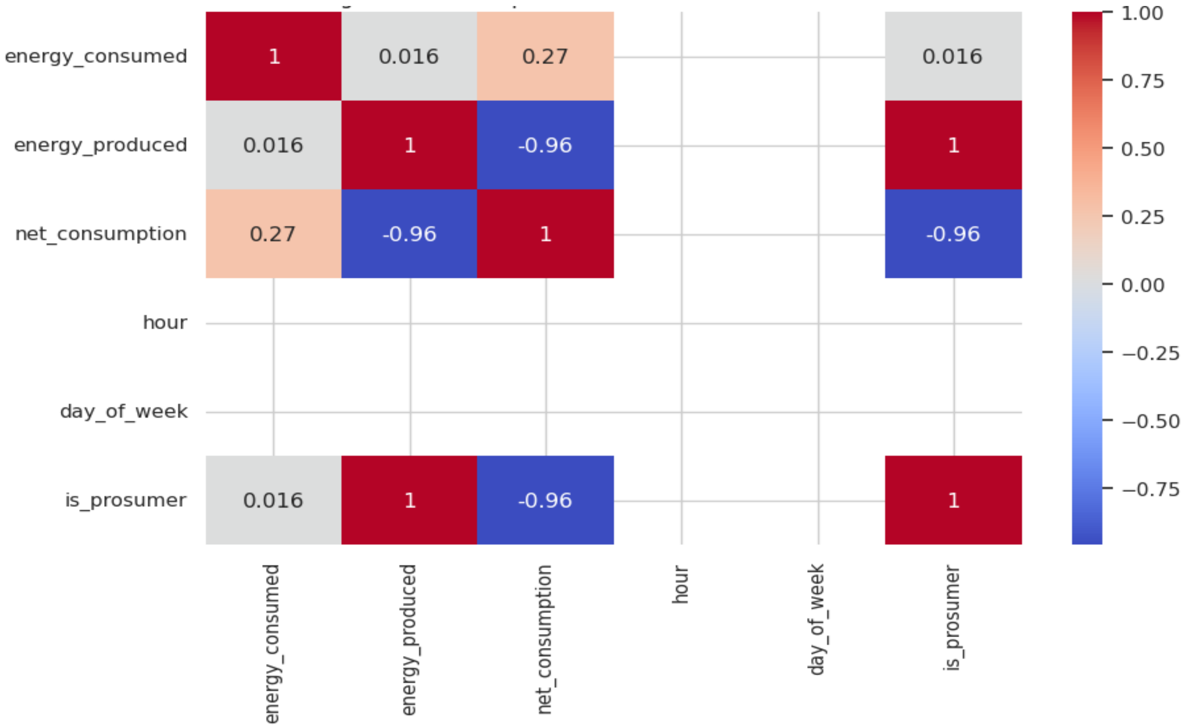



Figure 5-25: Heatmap of feature correlation in cluster

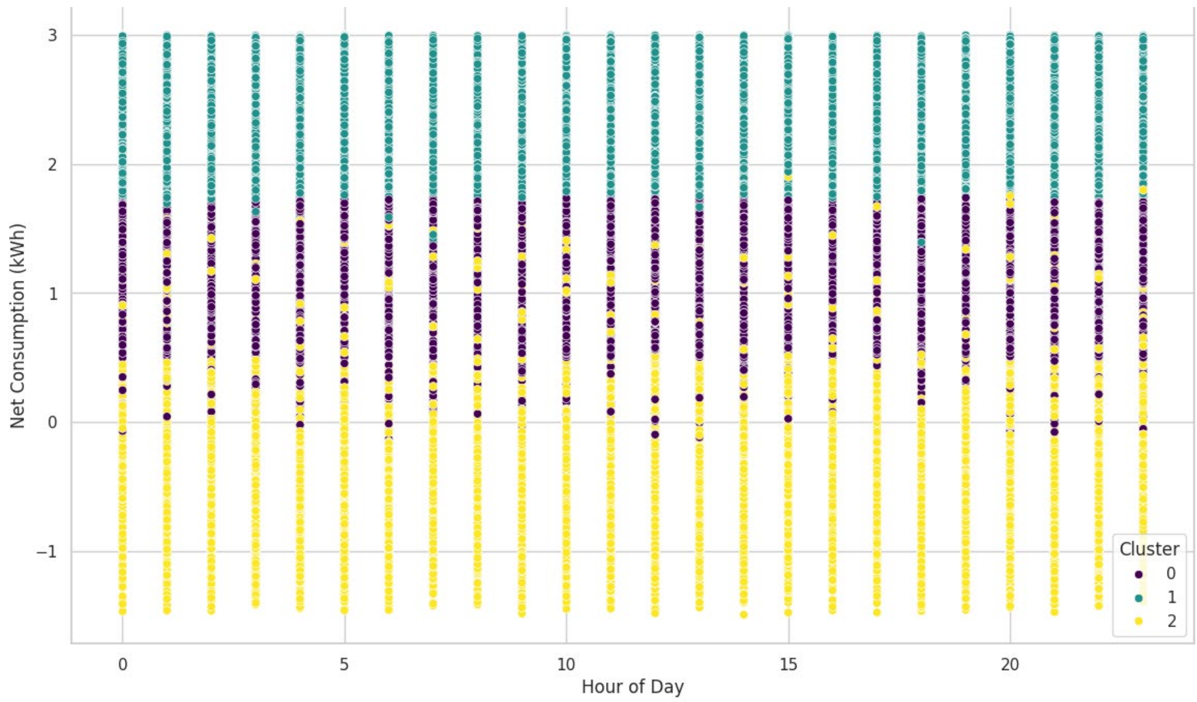



Figure 5-26: Clusters based on hourly net consumption

Figure 5-27 shows the distribution of net consumption across the clusters. This helps to understand how energy is consumed or generated by different customer types in the smart grid.

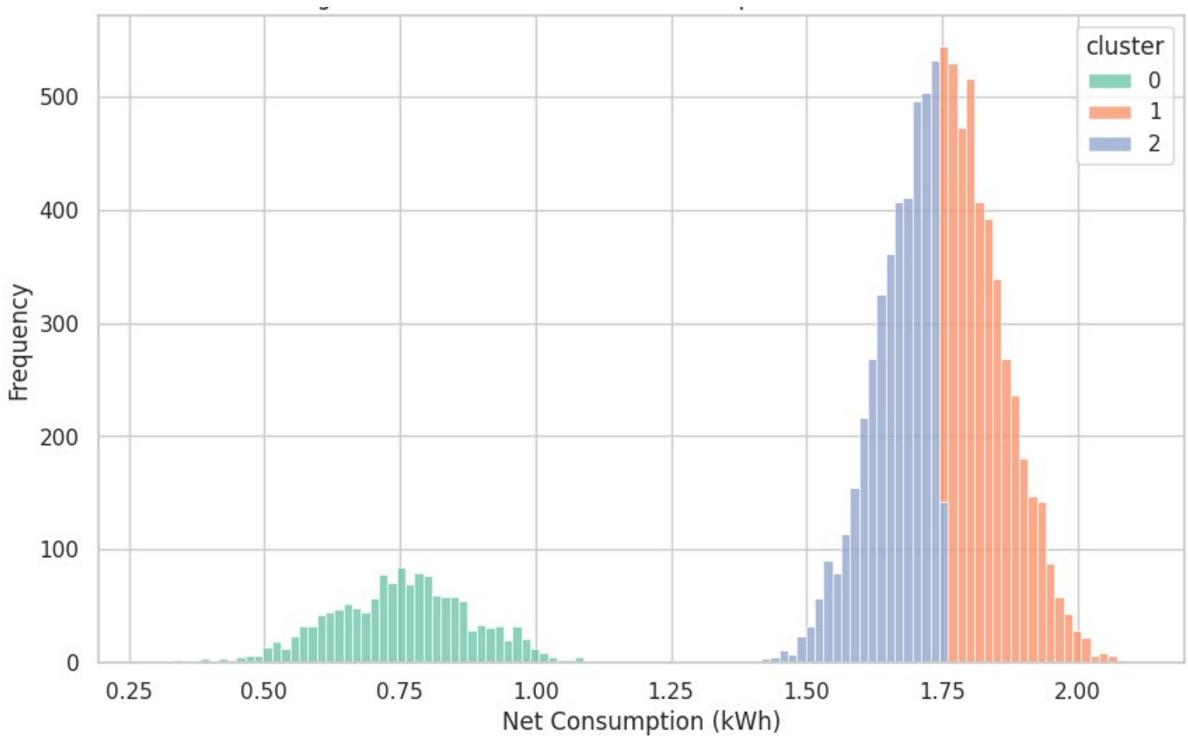



Figure 5-27: Distribution of net-consumption across clusters

### 5.10.7 Visualization and Analysis of Clusters

For the purpose of visualisation, the dataset's dimensionality was reduced using Principal Component Analysis (PCA). When the clusters were displayed in a two-dimensional space, different patterns between the customer groups were evident. This visualisation aided in comprehending the traits of every cluster and provided guidance for creating the DNN prediction models.

## 5.11 Deep Neural Network for Energy Prediction

### 5.11.1 Neural Network Architecture

To capture the intricate interactions between input data and the target variables (energy production and consumption), a multilayer deep neural network was constructed. Which made up the architecture was:

- **Input Layer**: Accepting the standardized features of each customer.
- **Hidden Layers**: Composed of ReLU activation functions-equipped thick (completely linked) layers that allow the model to learn nonlinear relationships.
- **Output Layer**: Estimating the amount of energy produced and consumed over a 24-hour period.

### 5.11.2 Training and Evaluation

The backpropagation technique with an Adam optimiser was used to train the DNN. Mean Absolute Error (MAE) was the evaluation measure, while Mean Squared Error (MSE) was the loss function. To avoid overfitting, a piece of the training data was used to evaluate the model after the dataset was divided into training and testing sets. During training, the model's parameters were iteratively changed across a number of epochs in order to minimise loss. To make sure the model performs effectively when applied to previously unseen data, it was tested on the test set after training. The flowchart of DNN implementation is showing in Figure 5-28.

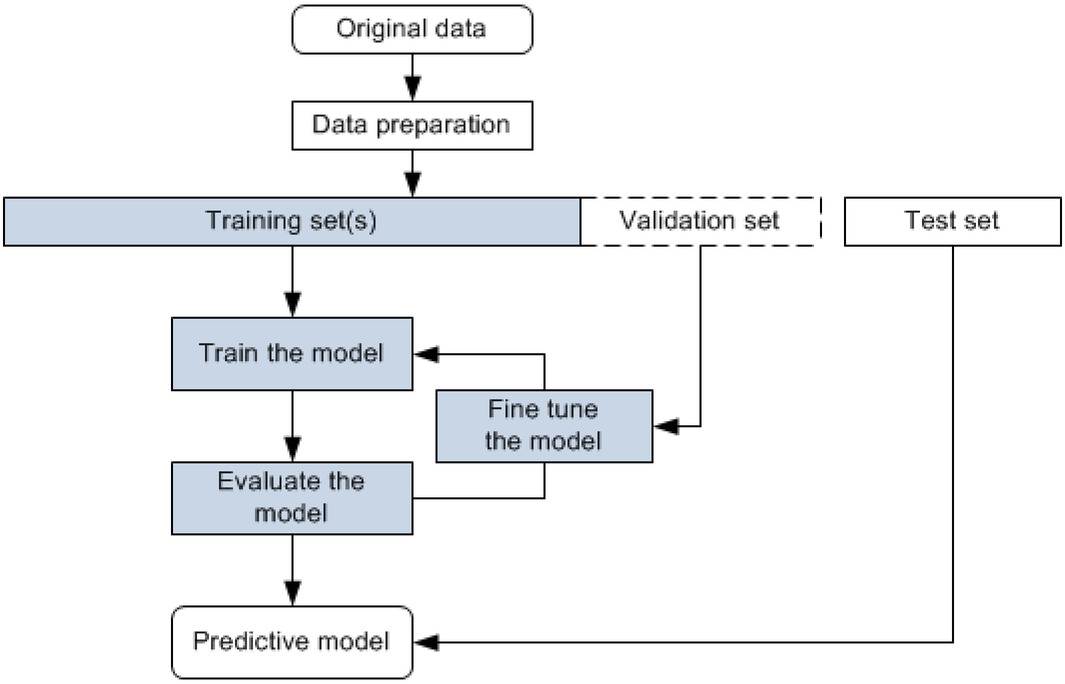



Figure 5-28: Flowchart for DNN implementation

### 5.11.3 Prediction Results and Analysis

The DNN performed well in estimating each cluster's hourly energy production and consumption. With only small variations brought about by the inherent unpredictability of energy use, the projections and actual values were rather similar. MAE was used to measure the model's accuracy, and the results showed how well the model captured the patterns in energy consumption. For five consumers and for five prosumers the actual and predicted energy values are showing in the graphs below, from Figure 5-29 to Figure 5-33 are the actual and predicted energy values for the consumers, however for each consumer the total energy consumption during a day and it's prediction is also find after the each figure, and also how much energy is required to achieve the net zero state. In Table 5-9 and Figure 5-39 there is the overall net consumption of all customers including consumers and prosumers, so in this way, it’s possible to calculate the net production which is needed to meet the zero energy concept.

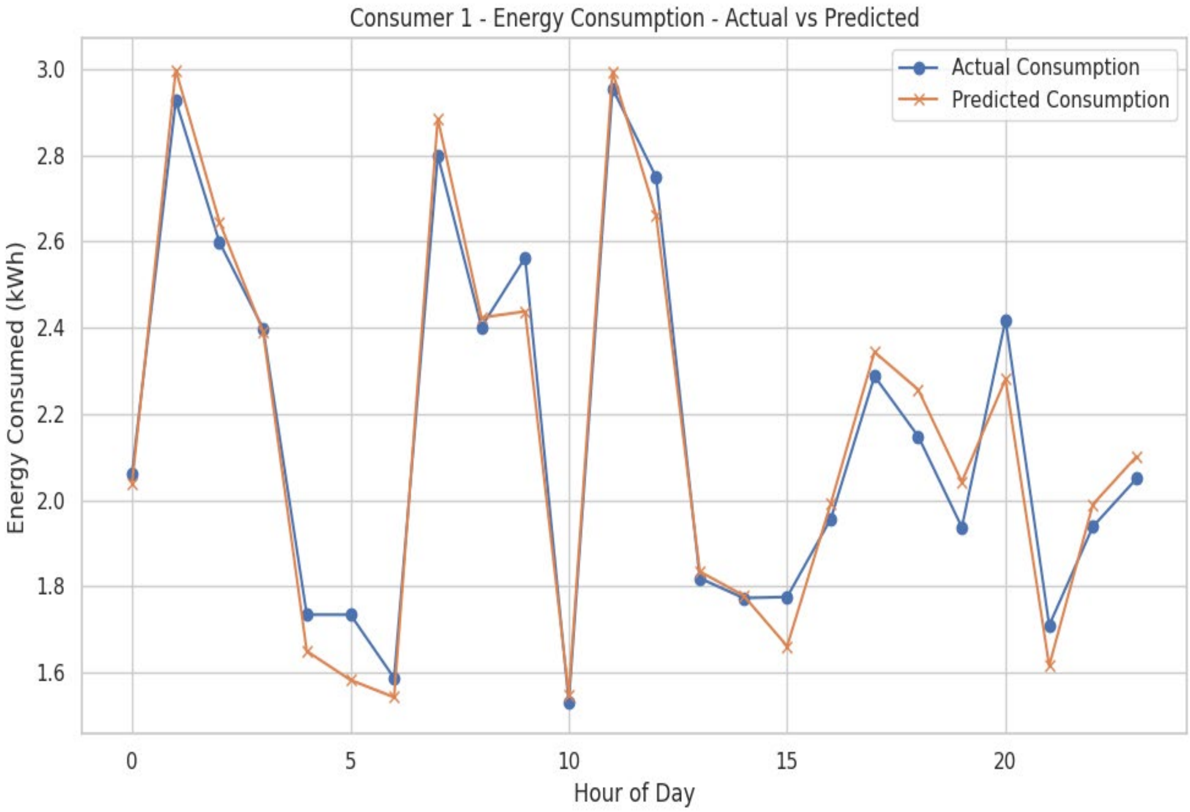



Figure 5-29: Energy consumption for consumer-1

```
Consumer 1 - Total Actual Consumption: 51.846 kWh
Consumer 1 - Total Predicted Consumption: 51.688 kWh
Consumer 1 - Energy Required to Achieve Net Zero: 51.846 kWh
```

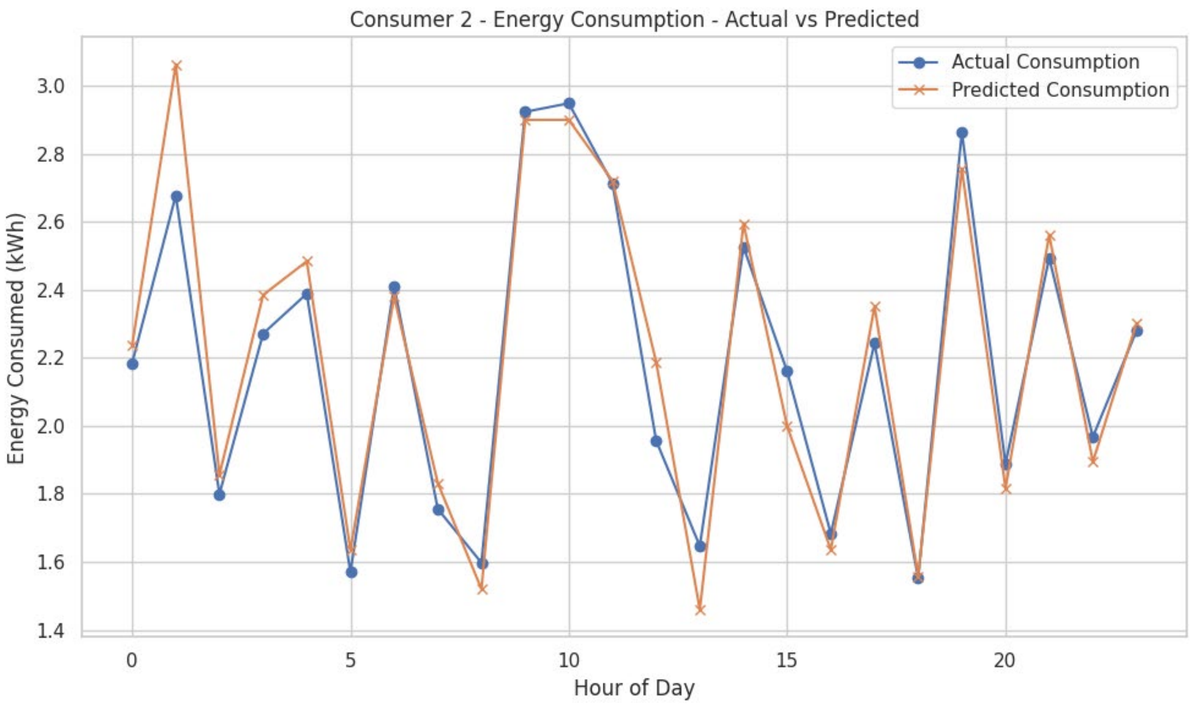



Figure 5-30: Energy consumption for consumer-2

```
Consumer 2 - Total Actual Consumption: 52.501 kWh
Consumer 2 - Total Predicted Consumption: 53.030 kWh
Consumer 2 - Energy Required to Achieve Net Zero: 52.501 kWh
```

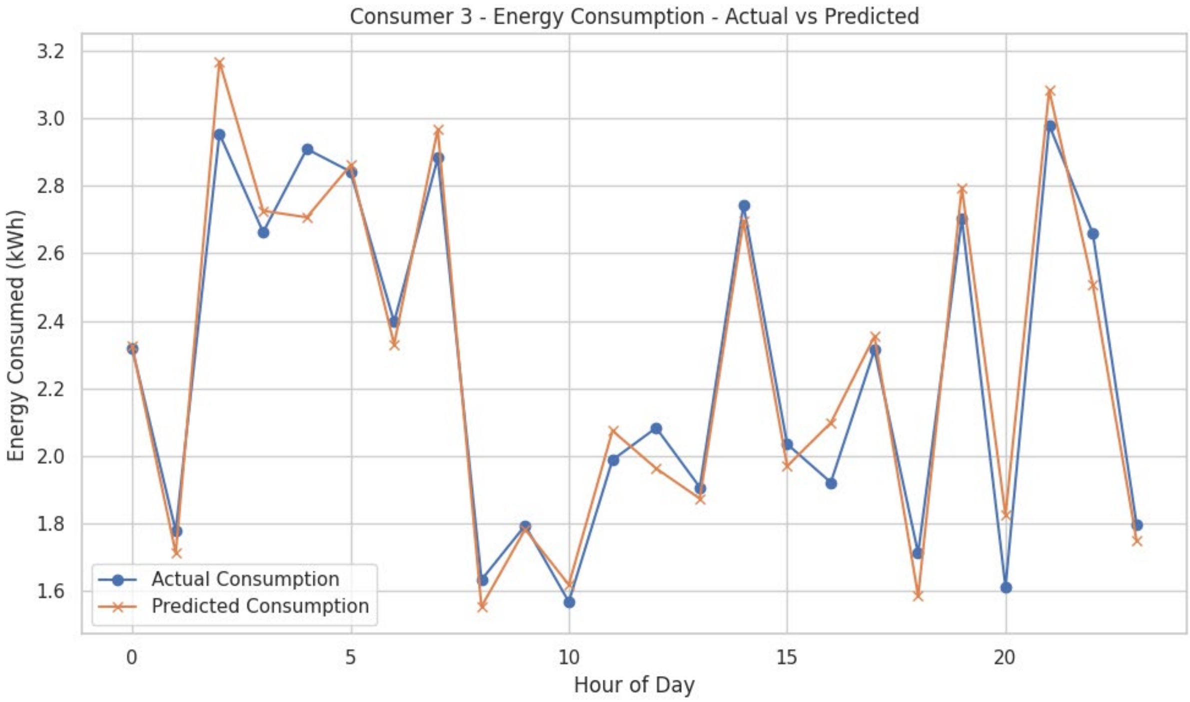



Figure 5-31: Energy consumption for consumer-3

```
Consumer 3 - Total Actual Consumption: 54.195 kWh
Consumer 3 - Total Predicted Consumption: 54.325 kWh
Consumer 3 - Energy Required to Achieve Net Zero: 54.195 kWh
```

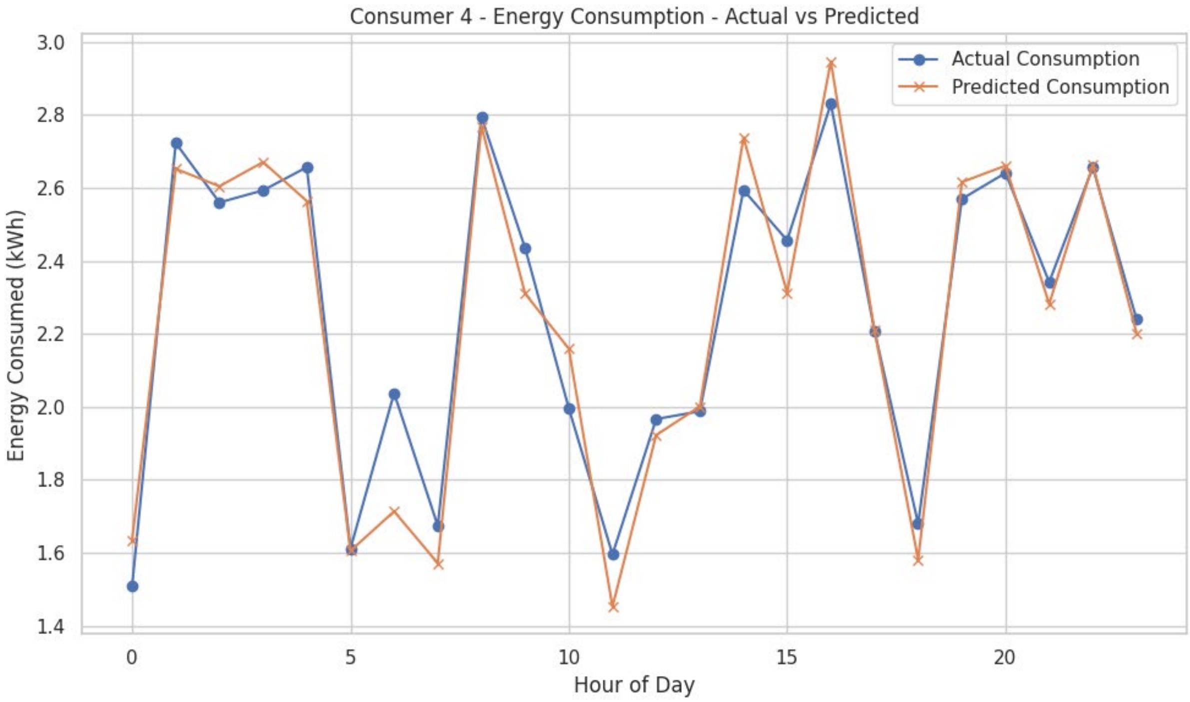



Figure 5-32: Energy consumption for consumer-4

```
Consumer 4 - Total Actual Consumption: 54.360 kWh
Consumer 4 - Total Predicted Consumption: 53.846 kWh
Consumer 4 - Energy Required to Achieve Net Zero: 54.360 kWh
```

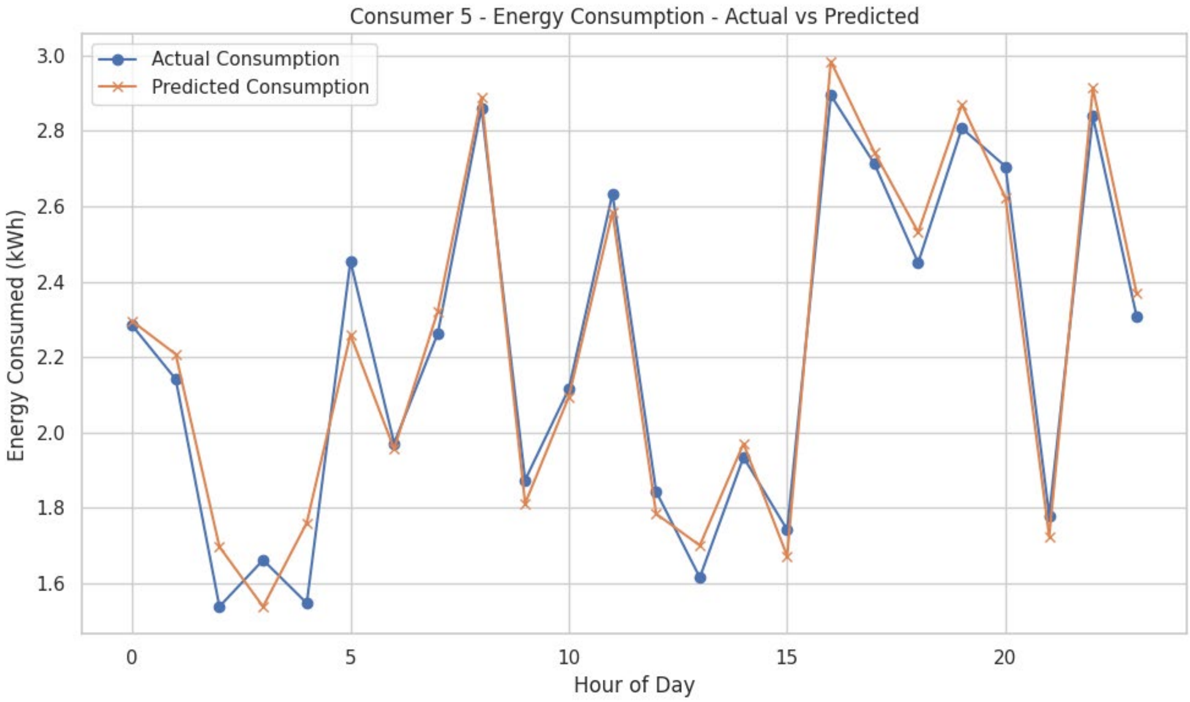



Figure 5-33: Energy consumption for consumer-5

```
Consumer 5 - Total Actual Consumption: 52.978 kWh
Consumer 5 - Total Predicted Consumption: 53.302 kWh
Consumer 5 - Energy Required to Achieve Net Zero: 52.978 kWh
```

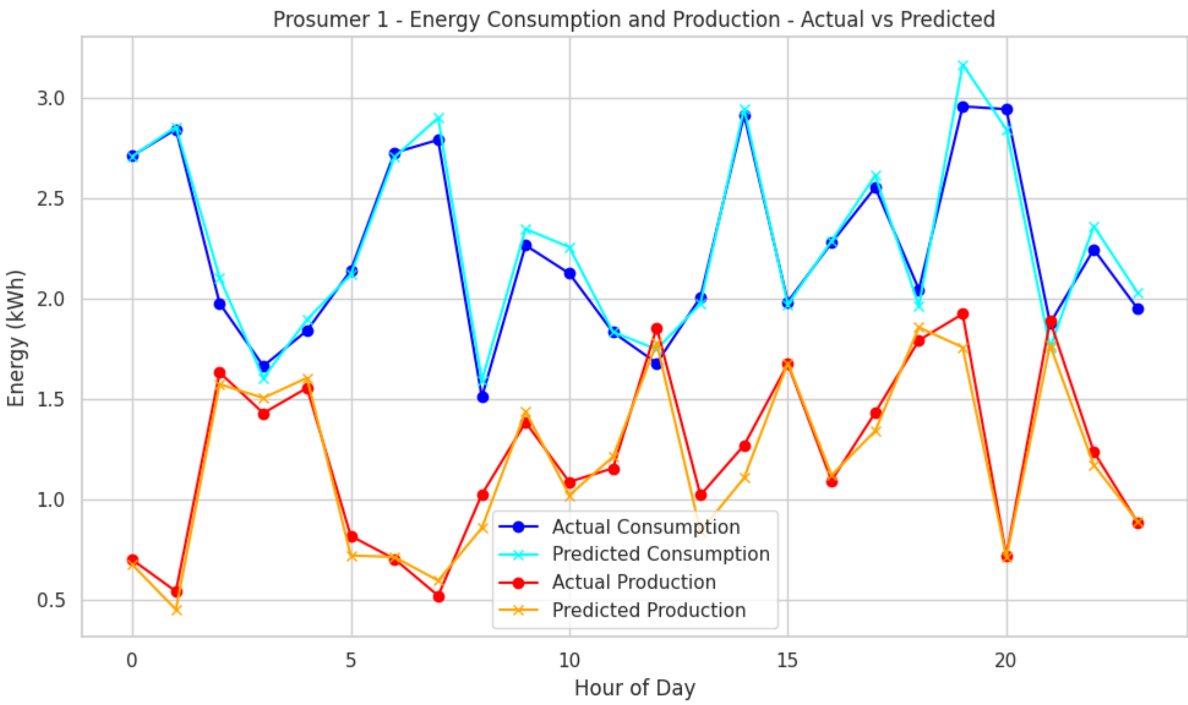



Figure 5-34: Energy consumption for prosumer-1

```
Prosumer 1 - Total Actual Consumption: 53.874 kWh
Prosumer 1 - Total Predicted Consumption: 54.597 kWh
Prosumer 1 - Total Actual Production: 29.372 kWh
Prosumer 1 - Total Predicted Production: 28.421 kWh
Prosumer 1 - Energy Required to Achieve Net Zero: 24.502 kWh
```

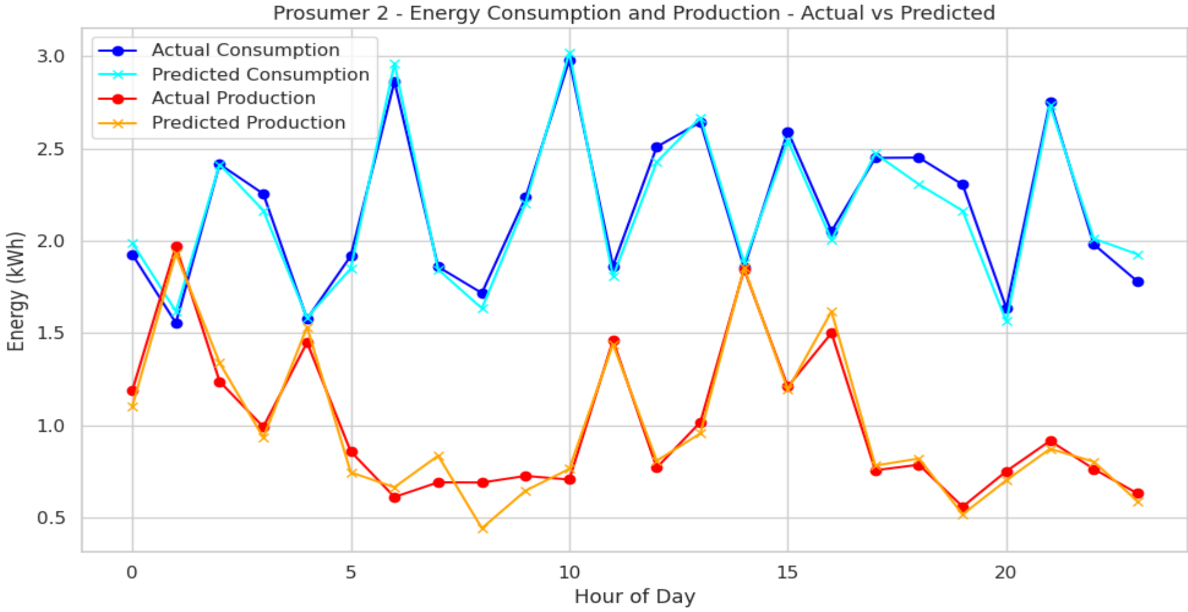



Figure 5-35: Energy consumption for prosumer-2

```
Prosumer 2 - Total Actual Consumption: 52.164 kWh
Prosumer 2 - Total Predicted Consumption: 51.783 kWh
Prosumer 2 - Total Actual Production: 24.125 kWh
Prosumer 2 - Total Predicted Production: 23.931 kWh
Prosumer 2 - Energy Required to Achieve Net Zero: 28.039 kWh
```

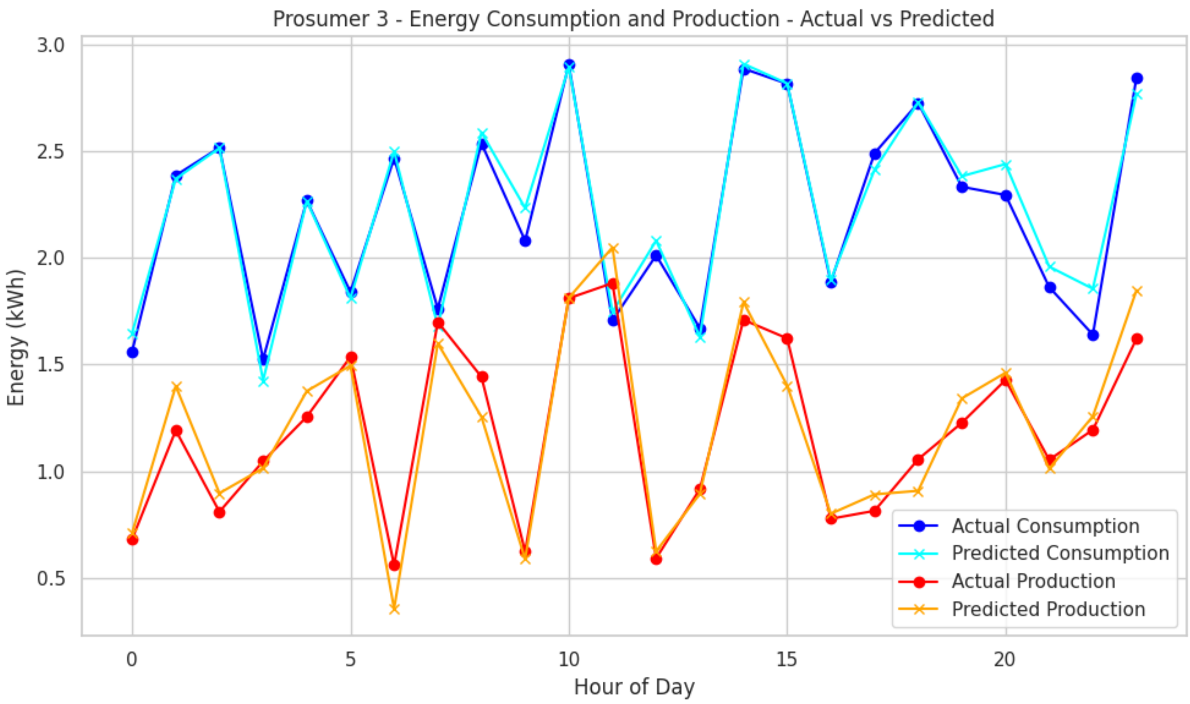



Figure 5-36: Energy consumption for prosumer-3

```
Prosumer 3 - Total Actual Consumption: 53.017 kWh
Prosumer 3 - Total Predicted Consumption: 53.555 kWh
Prosumer 3 - Total Actual Production: 28.541 kWh
Prosumer 3 - Total Predicted Production: 28.776 kWh
Prosumer 3 - Energy Required to Achieve Net Zero: 24.476 kWh
```

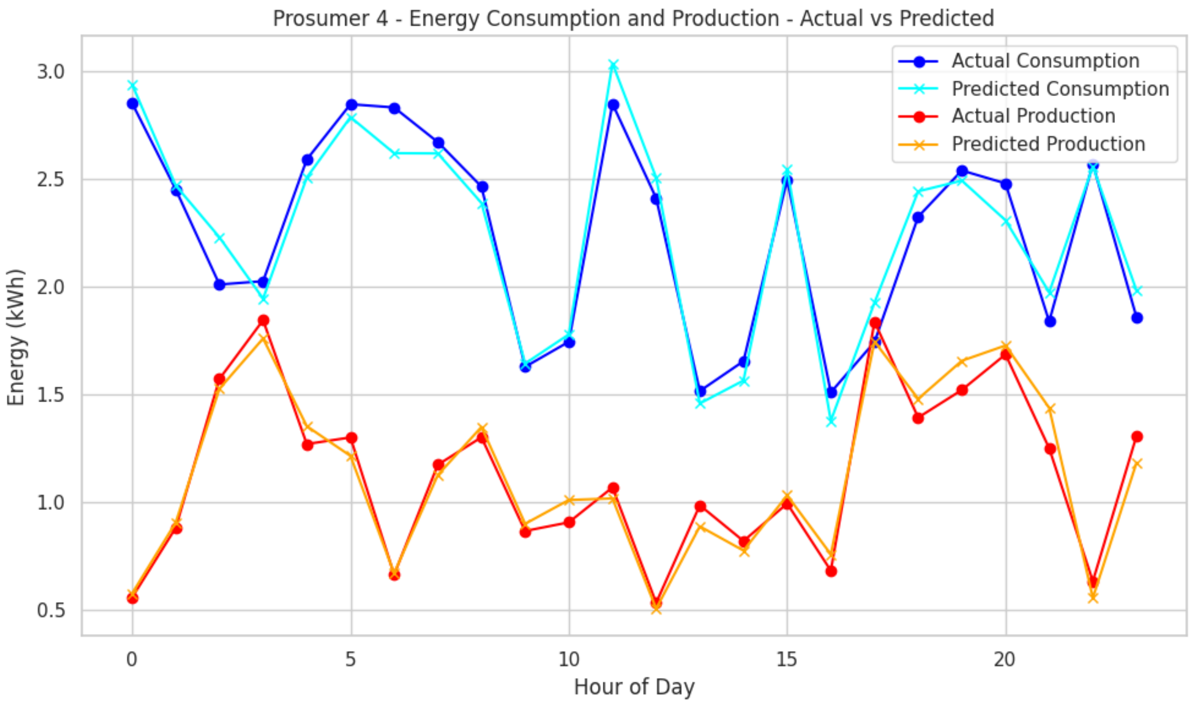



Figure 5-37: Energy consumption for prosumer-4

```
Prosumer 4 - Total Actual Consumption: 53.866 kWh
Prosumer 4 - Total Predicted Consumption: 54.057 kWh
Prosumer 4 - Total Actual Production: 26.990 kWh
Prosumer 4 - Total Predicted Production: 27.095 kWh
Prosumer 4 - Energy Required to Achieve Net Zero: 26.876 kWh
```

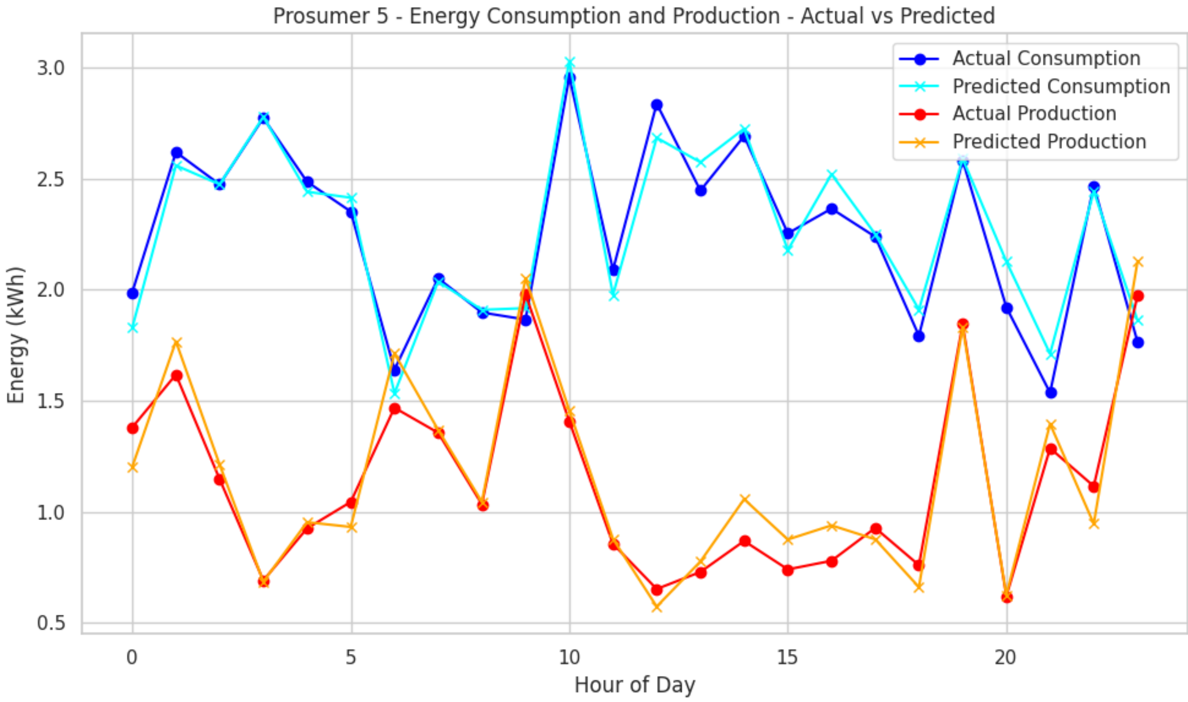



Figure 5-38: Energy consumption for prosumer-5

```
Prosumer 5 - Total Actual Consumption: 54.103 kWh
Prosumer 5 - Total Predicted Consumption: 54.485 kWh
Prosumer 5 - Total Actual Production: 27.212 kWh
Prosumer 5 - Total Predicted Production: 27.957 kWh
Prosumer 5 - Energy Required to Achieve Net Zero: 26.891 kWh
```

Table 5-9: Total consumption and production for five consumers and prosumers

```
Summary Table:
       Type     Customer  Total Actual Consumption (kWh)  \
0  Consumer  Consumer 1                          51.846
1  Consumer  Consumer 2                          52.501
2  Consumer  Consumer 3                          54.195
3  Consumer  Consumer 4                          54.360
4  Consumer  Consumer 5                          52.978
5  Prosumer  Prosumer 1                          53.874
6  Prosumer  Prosumer 2                          52.164
7  Prosumer  Prosumer 3                          53.017
8  Prosumer  Prosumer 4                          53.866
9  Prosumer  Prosumer 5                          54.103

   Total Predicted Consumption (kWh)  Total Actual Production (kWh)  \
0                             51.688                          0.000
1                             53.030                          0.000
2                             54.325                          0.000
3                             53.846                          0.000
4                             53.302                          0.000
5                             54.597                         29.372
6                             51.783                         24.125
7                             53.555                         28.541
8                             54.057                         26.990
9                             54.485                         27.212

   Total Predicted Production (kWh)  Net Zero Required (kWh)
0                             0.000                   51.846
1                             0.000                   52.501
2                             0.000                   54.195
3                             0.000                   54.360
4                             0.000                   52.978
5                            28.421                   24.502
6                            23.931                   28.039
7                            28.776                   24.476
8                            27.095                   26.876
9                            27.957                   26.891
```

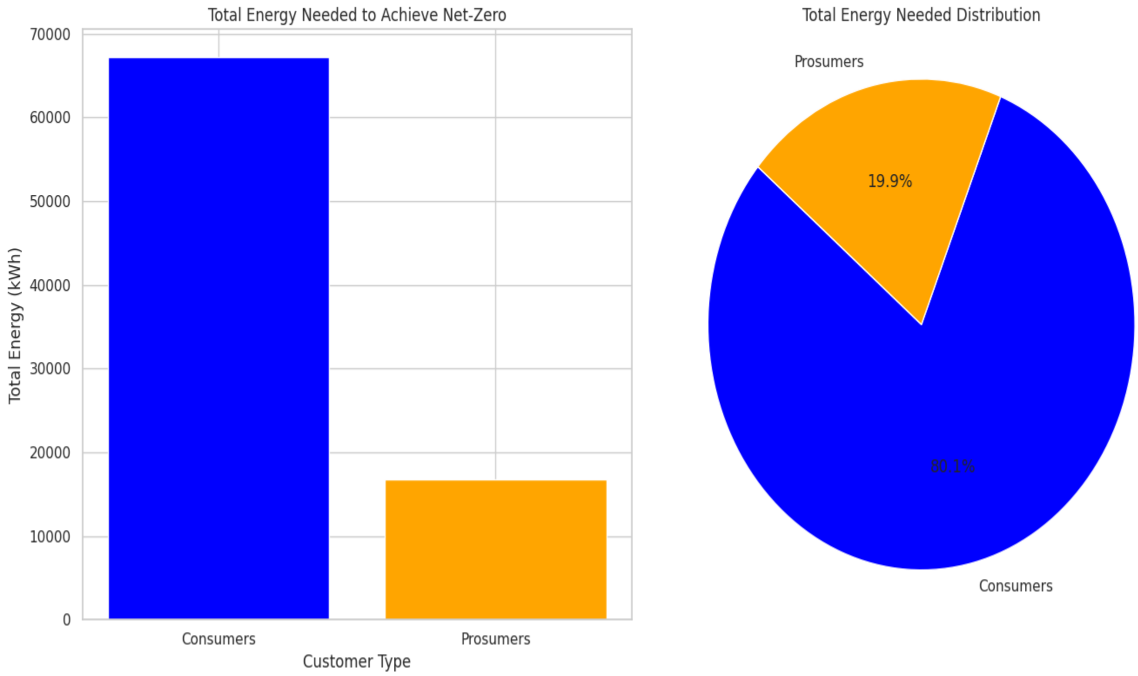



Figure 5-39: Overall net consumption and production of customers

## 5.12 Renewable Energy Sources and Their Role in Achieving Net Zero

Achieving net zero energy consumption requires the use of renewable energy sources, including wind, solar, and other sources. These renewable energy sources minimise the need to use the grid by producing clean, sustainable energy that can be stored in batteries for later use. To investigate how these renewable sources help to reaching net zero, the electrical grid model integrates them as shown in Figure 5-40.

### 5.12.1 Solar Energy Integration

The abundance of solar energy and the declining cost of photovoltaic (PV) systems make it one of the most popular renewable energy sources. Residential and business properties are equipped with solar panels in the model. These panels produce energy during the day, which can be stored in the battery for later use or used right away to power the loads.

Managing the electricity produced by the solar panels is largely the responsibility of the DNN. The system is instructed to store excess energy in the battery when it anticipates periods of strong solar generation and low demand. To lessen dependency on the grid, this stored energy is subsequently used at night or in the evening when solar power is not available. The DNN assists the system in approaching net zero energy usage by maximising the use of solar energy.

### 5.12.2 Wind Energy Integration

Another important renewable energy source that complements solar energy is wind energy. While solar generation may be low during overcast or windy weather, wind generation is typically higher at night. The DNN also controls the wind turbines in the MATLAB/Simulink model, which produce power.

Through wind pattern prediction and energy storage strategy adjustment, the DNN maximises wind energy utilisation. The DNN may, for example, decide to discharge the battery in the evening (at a time when wind generation is lower) and recharge it with wind energy overnight if strong winds are forecast. This tactic guarantees that renewable energy is utilised to its maximum capacity, hence decreasing reliance on the grid.

### 5.12.3 Hybrid Renewable Systems

A renewable energy system that combines wind and solar power is more dependable and resilient. The DNN in the model, which constantly adapts to the availability of both inputs, is in charge of this hybrid method. When it's sunny and windy outside, for instance, the DNN might prefer to use solar energy for immediate use and store wind energy in the battery for use when solar power declines.

The DNN improves the system's capacity to reach net zero energy by efficiently managing these hybrid systems. By maximising renewable generation and reducing times when the system needs rely on the grid, the combined use of solar and wind energy makes it easier to achieve net zero energy usage.

## 5.13 Strategies for Achieving Net Zero Energy Consumption

In the MATLAB/Simulink model, achieving net zero energy consumption necessitates the intelligent management of demand, the strategic application of renewable energy sources, and optimised energy storage. The next tactics illustrate how the model can be modified to accomplish this objective.

### 5.13.1 Maximizing Renewable Energy Utilization

The main approach to reaching net zero is to use as much renewable energy as possible. Because it forecasts renewable energy generation and matches it with load demand, the DNN is essential to this process. For example, the DNN makes sure that solar energy is stored in the battery or consumed directly by the loads on days with high solar irradiation, therefore preventing waste. Similar to this, wind energy is captured and stored for later use when it's windy. The neural network architecture selection is showing in Figure 5-41.

Demand-side management strategies can be incorporated into the model to further improve the utilisation of renewable energy. This involves rearranging energy-intensive tasks (such charging electric cars and running appliances) to coincide with periods of high renewable generation, which lowers the demand for grid energy.

### 5.13.2 Optimising Battery Storage

Achieving net-zero energy goals requires effective management of battery storage systems. By predicting optimal charge and discharge times based on energy demand and renewable energy generation forecasts, the DNN optimises battery performance. For example, the DNN may schedule discharging during peak demand periods, such as evenings when renewable energy output is lower, and prioritize charging during midday when solar energy production is at its highest.

The DNN can also be trained to minimize energy losses during the storage and retrieval process, thereby enhancing the overall efficiency of the system. This approach not only optimises battery utilization but also reduces dependence on the grid, contributing to a more sustainable energy system.

### 5.13.3 Implementing Demand Response

Demand response systems adjust energy consumption patterns in response to the availability of renewable energy or real-time grid signals. In the MATLAB/Simulink model, the DNN shifts non-essential loads to periods when renewable energy generation is at its peak, effectively managing demand response. For example, the DNN may delay the operation of certain appliances until the battery is fully charged or renewable energy production reaches its maximum.

By incorporating demand response, the system can further decrease its reliance on the grid, bringing it closer to achieving net-zero energy. This strategy also helps to manage peak loads, reducing pressure on the grid and enhancing overall grid stability.

### 5.13.4 Hybrid Energy Systems and Grid Interaction

While the goal is to achieve net-zero energy, there may still be instances where renewable energy generation is insufficient to meet demand, even with optimised battery storage. In such scenarios, the DNN manages the interaction between the grid and the hybrid energy system, which includes solar, wind, and battery resources, to maintain system reliability and minimize grid dependency.

For example, during extended periods of low renewable output, such as a cloudy and calm day, the DNN may allow limited grid usage to meet energy demands. However, it ensures that grid energy is used sparingly and efficiently, only when absolutely necessary, maintaining a balance between grid interaction and the use of renewable resources.

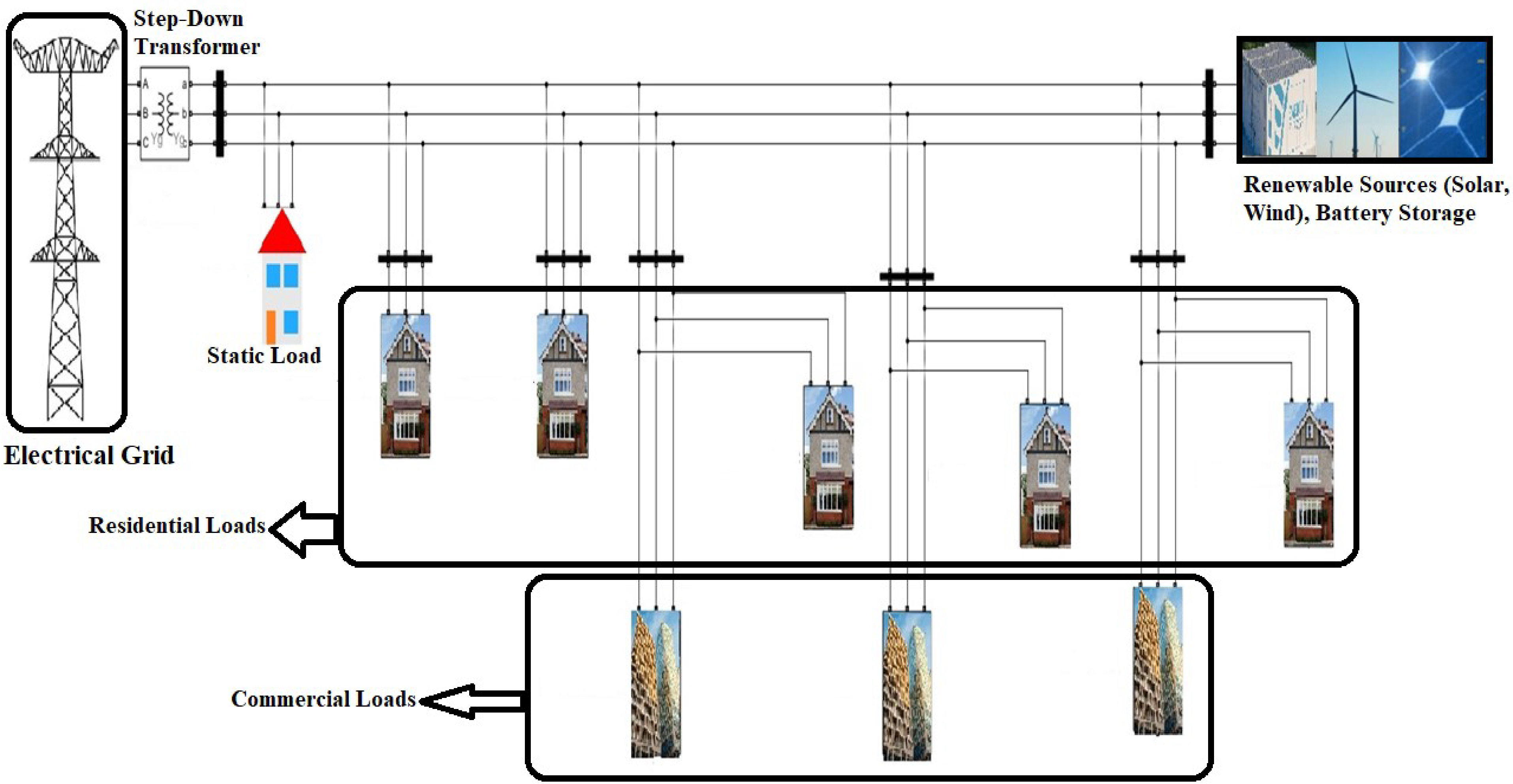



Figure 5-40: The Proposed Electrical Model with the integration of RES, grid and loads

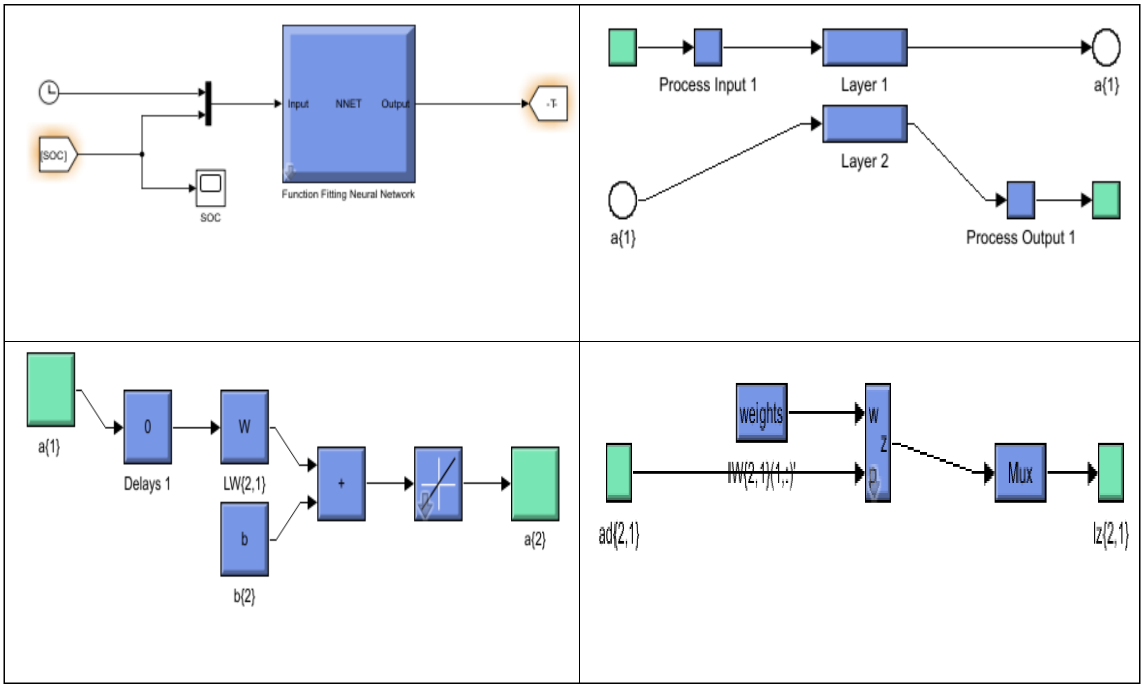
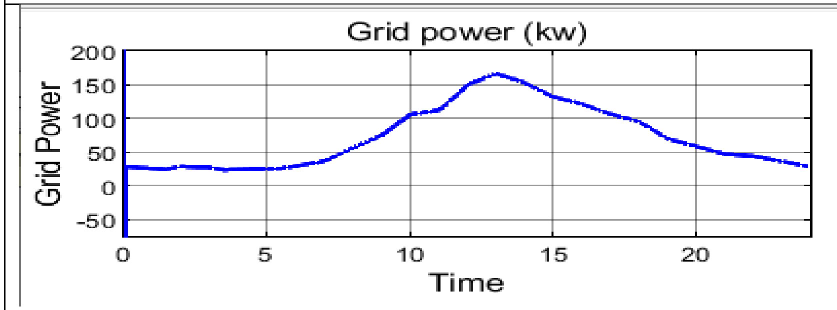
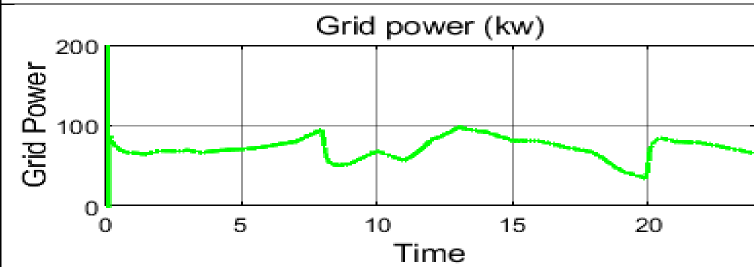
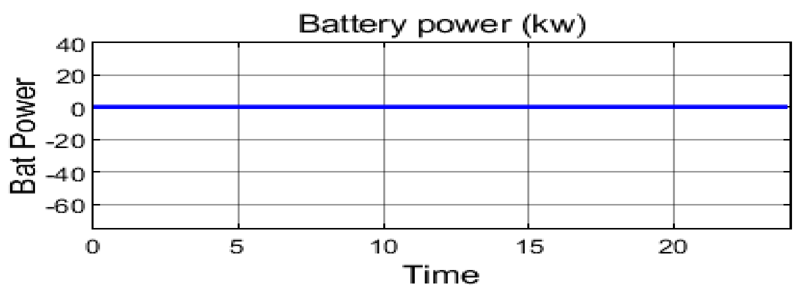
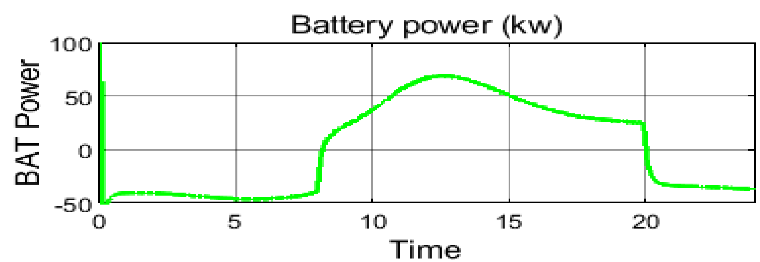
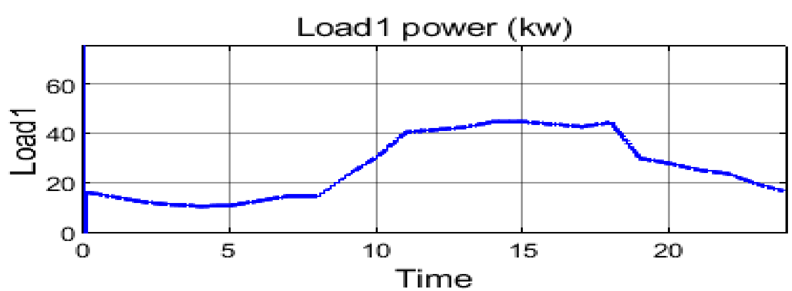
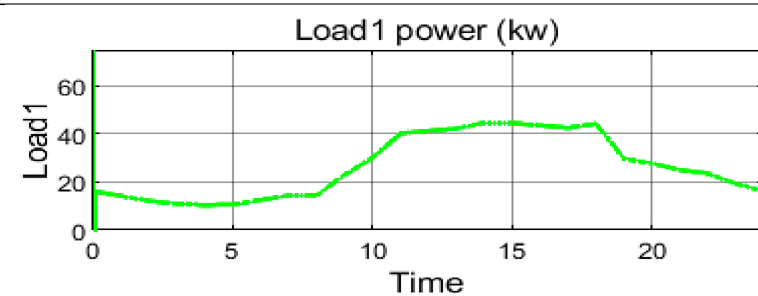
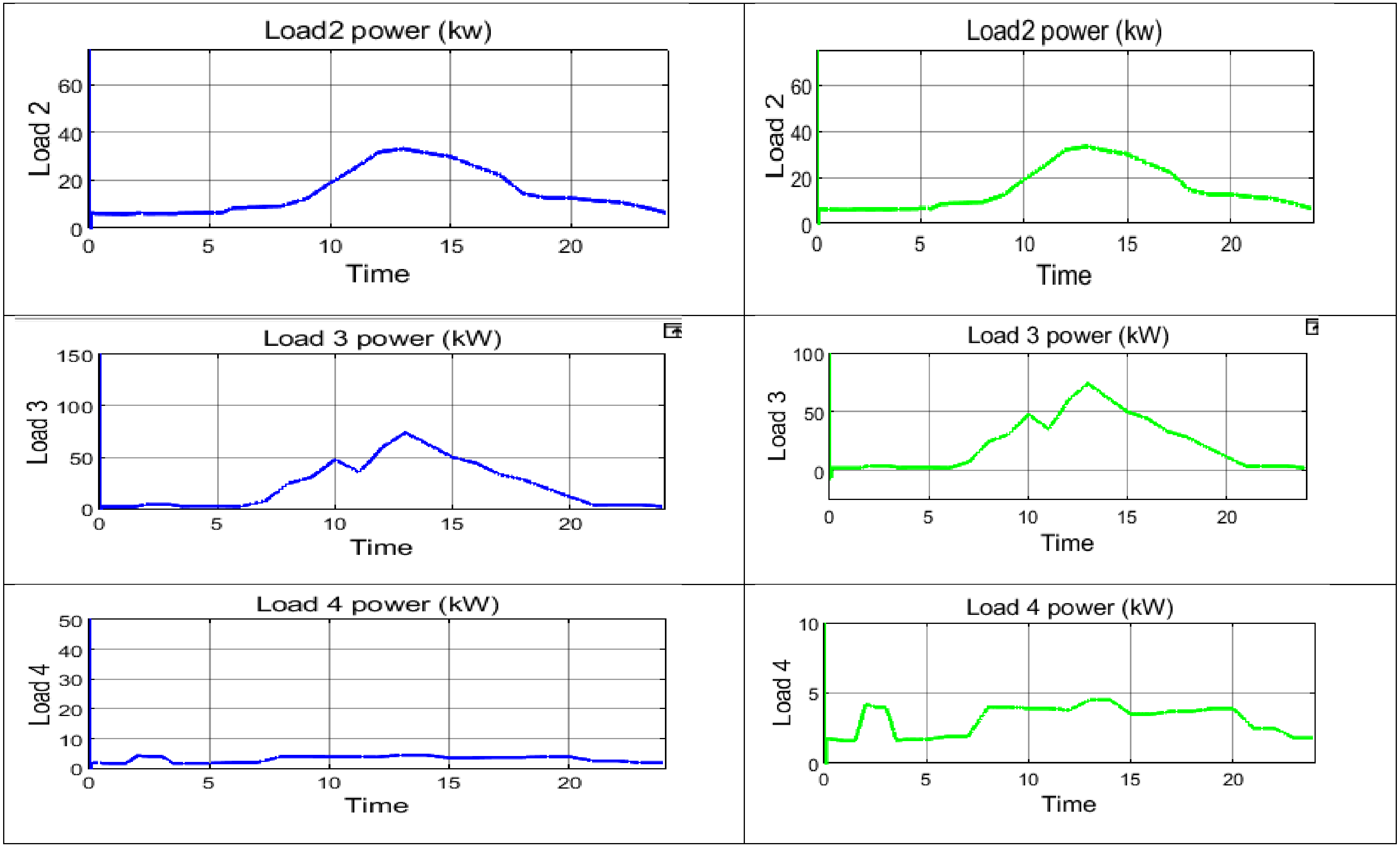



Figure 5-41: Neural Network architecture selection

**Comparison of energy consumption and production for grid, loads and renewable energy storage**

| Grid-Connected without Renewable Sources | Grid-Connected with Renewable Sources |
|---|---|
|  |  |
|  |  |
|  |  |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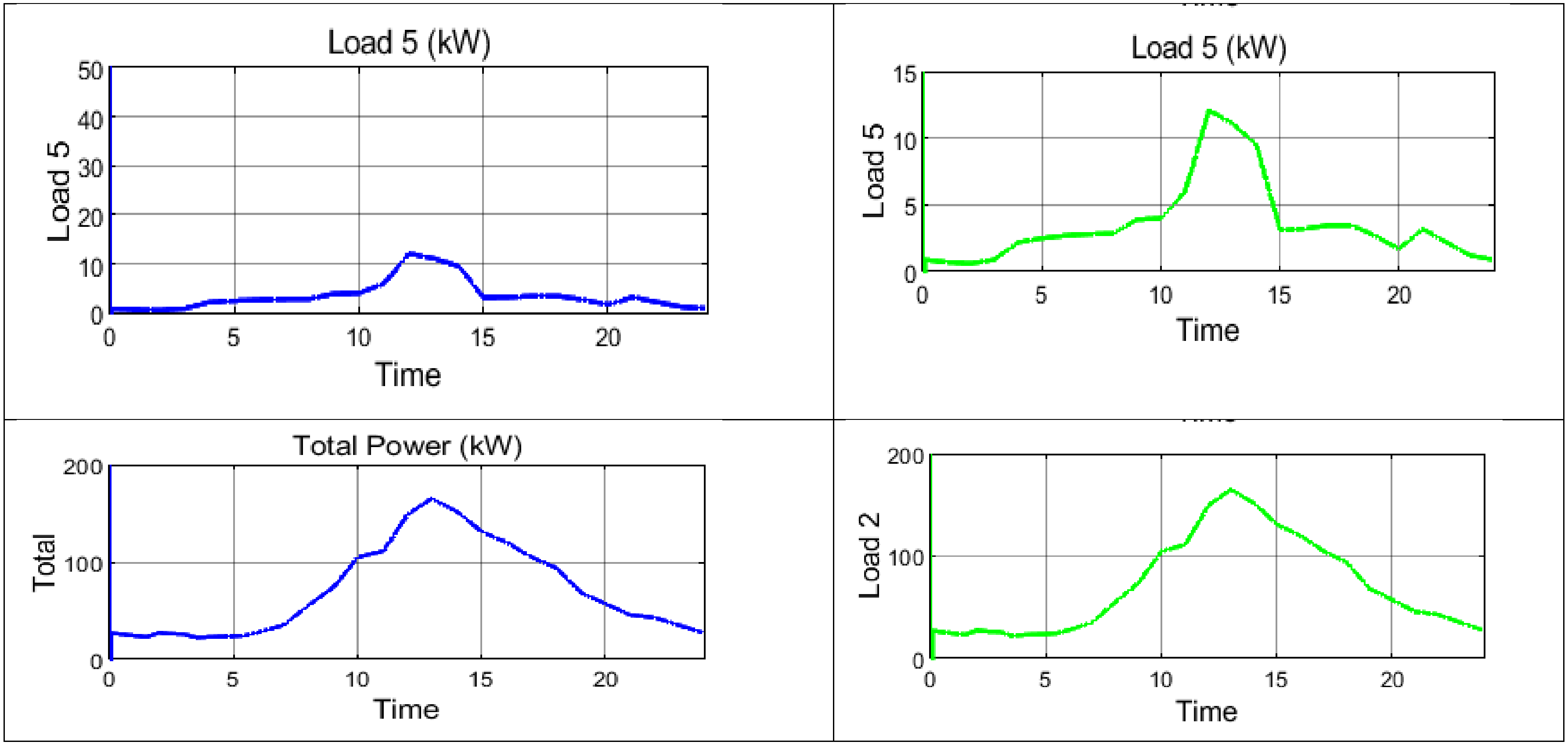

Figure 5-42: Comparison of energy consumption and production for grid, loads and renewable energy storage

## 5.14 Discussion and Future Work

### 5.14.1 Discussion of Results

Demand-side energy in a smart grid was successfully managed by the application of the DNN-based optimisation framework. Accurate energy usage forecasts were produced by the DNN, and clustering enabled focused predictions and optimisations. Even though the optimisation technique was straightforward, it showed notable gains in reaching net-zero energy.

In Figure 5-42 it's clearly shows that, when the system is not connected with the battery storage and renewable energy sources, then all the loads are using the energy from grid, but when there is an integration of renewable sources and battery storage with the system, then the energy consumption from the grid side is minimum and all the loads are using the energy from renewable sources, however the total power is remain same in both cases. In this way we can predict that how much energy can be required to achieve the net zero to make the system more optimised and efficient.

Achieving net-zero energy goals requires effective management of battery storage systems. By predicting optimal charge and discharge times based on energy demand and renewable energy generation forecasts, the DNN optimises battery performance. For example, the DNN may schedule discharging during peak demand periods, such as evenings when renewable energy output is lower, and prioritize charging during midday when solar energy production is at its highest.

The DNN can also be trained to minimize energy losses during the storage and retrieval process, thereby enhancing the overall efficiency of the system. This approach not only optimises battery utilization but also reduces dependence on the grid, contributing to a more sustainable energy system.

### 5.14.2 Limitations

Although the existing framework produced encouraging results, a number of drawbacks were found:

- **Scalability**: The scalability of the framework in real life requires more research, as it was tested on a synthetic dataset.

- **Real-time Adaptation**: When energy output or consumption suddenly changes, the existing model is unable to adjust in real time.

### 5.14.3 Future Work

Future developments will concentrate on integrating the framework with actual smart grid systems to increase its scalability. To enhance real-time adaptability, further research will be done on sophisticated optimisation methods like reinforcement learning. Lastly, the forecasts and optimisations could be improved even more by adding more detailed data, including minute-by-minute energy usage.

## 5.15 Summary of Chapter

For clustering demand-side energy management in smart grids, this chapter described the architecture and implementation of an optimisation framework based on DNNs. The framework made significant progress towards the objective of attaining net-zero energy in smart grids by integrating clustering techniques with deep learning and optimisation tactics to facilitate efficient management of energy production and consumption. These showed that the suggested solution could improve the sustainability and efficiency of smart grids in the future.

This chapter has shown how net zero energy consumption can be achieved in a smart grid setting by integrating deep neural networks, renewable energy sources, and strategic energy management. The MATLAB/Simulink model efficiently minimises grid dependency by utilising DNNs for predictive control and optimisation, especially when battery storage is used.

The proposed research of DSEM is essential to meet the energy requirements especially in SG with integrated RES at supplier and consumer side. To fulfil the DSEM requirements, energy prediction is also one of the main steps to meet the requirements of consumers in a specific interval of time. Neural Network technique is best and efficient to predict the energy requirements to optimise the entire electrical system in aspect of energy management.  The descriptive results showing that, the prediction of energy is precise according to the daily dataset of consumers. Similarly, neural network can be able to detect the energy prediction on weekly, monthly, seasonal, and yearly basis to meet the concept of DSEM.

Renewable energy sources will be integrated into an electrical network, a systematic approach involves resource assessment, load analysis, and spatial planning to form clusters based on geographical and electrical characteristics. The selection of appropriate renewable technologies, microgrid design, and integration of energy storage systems are crucial for managing variability. Smart grid technologies enhance real-time control, and interconnections with the main grid ensure flexibility. Compliance with local regulations, community engagement, and a focus on monitoring, maintenance, training, and capacity building contribute to the successful creation and sustainable operation of these integrated renewable energy clusters.

# Chapter 6: Conclusion

This research presents a comprehensive exploration of Deep Neural Network (DNN)-based optimisation strategies for enhancing clustered demand-side energy management (CDEM) in smart grid environments. The study focused on designing, implementing, and evaluating advanced DNN models to predict energy consumption, optimise renewable energy integration, maintain grid stability, and detect anomalies such as faults and fraudulent behaviour. Through this work, significant advancements in the application of deep learning for smart grid operations have been demonstrated, contributing to the development of scalable, intelligent, and reliable energy management systems that support the global transition to net-zero energy.

The updated literature review in **Chapter 2** offers an extensive comparative analysis of existing energy optimisation techniques, including Particle Swarm Optimization (PSO), Genetic Algorithm (GA), classical optimisation models, and other machine learning approaches. This review reveals that while heuristic and rule-based methods provide acceptable performance in specific scenarios, they fall short in handling the complexity, scalability, and dynamic nature of modern smart grids. Deep Neural Networks emerged as the most promising approach due to their ability to learn intricate, non-linear patterns in energy data and provide real-time predictive analytics. The review is supported by recent studies from the last five years, which confirm the superior accuracy, adaptability, and efficiency of DNNs in diverse energy management applications.

Building on this foundation, **Chapter 3** implemented and evaluated DNN models in various configurations, comparing their performance against PSO, GA, and other traditional approaches. The simulation results clearly established DNN as the most accurate and reliable model for forecasting energy consumption and grid behaviour. Furthermore, this chapter introduced a comparative analysis of DNN performance with and without data clustering using K-means. The results confirmed that clustering significantly enhances prediction accuracy, model stability, and error reduction when managing large-scale energy systems involving both consumers and prosumers. Clustered DNN models demonstrated lower mean absolute error (MAE), root mean square error (RMSE), and higher $R^2$ scores than their non-clustered counterparts, proving the effectiveness of grouping similar energy profiles prior to training.

**Chapter 4** extended the study by focusing on net-zero energy optimisation strategies. DNNs were employed to manage the integration of intermittent renewable energy sources such as solar and wind, alongside battery storage and demand response. By leveraging their forecasting capabilities, DNNs enabled more efficient scheduling and utilisation of renewable resources, reducing reliance on fossil-fuel-based generation. Case studies in residential and commercial settings validated the approach, showing measurable reductions in energy wastage and improved alignment between supply and demand. This chapter also focused on the application of DNNs for anomaly detection, including fault identification and fraud detection. In increasingly digital and decentralised grids, such capabilities are essential for operational security. The DNN-based detection systems achieved high accuracy in identifying faults and detecting abnormal behaviour such as energy theft or meter tampering, proving their robustness in both preventive and corrective maintenance frameworks.

**Chapter 5** addressed the control aspect of smart grids by implementing DNN-based solutions for voltage and frequency regulation. Ensuring grid stability in real time is critical, especially with high penetration of variable renewable sources. The results demonstrated that DNN controllers significantly outperform traditional Proportional-Integral-Derivative (PID) controllers in maintaining voltage and frequency within safe operational limits. The adaptability and rapid response of DNNs contributed to higher system reliability under both normal and stressed conditions.

In summary, this research has established the versatility, intelligence, and effectiveness of DNNs in multiple dimensions of smart grid energy management. From prediction and optimisation to control and security, DNNs offer a unified and scalable solution to meet the challenges of evolving energy systems. The integration of K-means clustering further amplifies their potential by tailoring models to user-specific consumption and generation behaviours, leading to more granular, efficient, and scalable demand-side management systems.

### Key Contributions

- **Enhanced Prediction and Energy Management:**
  DNNs outperformed PSO, GA, and classical techniques in predicting energy demand, achieving lower error margins and greater accuracy, especially when applied to clustered consumer and prosumer datasets.
- **Clustering-Enabled Scalability:**
  The use of K-means clustering prior to DNN training resulted in improved accuracy, reduced residual variance, and better model convergence, making it a highly effective strategy for large-scale energy systems.
- **Net-Zero Energy Optimisation:**
  DNNs provided real-time forecasts of renewable generation and consumption, supporting optimised scheduling of solar, wind, and storage assets. This directly contributes to the realisation of net-zero energy targets.
- **Superior Grid Control:**
  DNN controllers demonstrated faster and more accurate regulation of grid voltage and frequency than traditional PID systems, enhancing overall grid reliability.
- **Robust Fault and Fraud Detection:**
  DNN models accurately detected operational anomalies and fraudulent activities, offering utilities a practical solution for improving system integrity and reducing financial loss.

### Future Directions

Building upon the success of this research, future work may explore the integration of reinforcement learning (RL) and hybrid AI models to further enhance the adaptability and responsiveness of energy management systems. Additionally, applying DNNs in multi-agent energy environments, involving real-time interactions between numerous distributed entities, would provide deeper insights into their scalability and coordination capabilities. Finally, the use of real-world smart meter and substation data in training and validation phases will strengthen the deployment-readiness of these models, moving toward commercial-grade, intelligent grid infrastructure.

In conclusion, this research demonstrates that Deep Neural Networks, particularly when integrated with clustering strategies, offer a transformative framework for intelligent, scalable, and efficient demand-side energy management in smart grids. As the global energy landscape shifts toward decentralisation and net-zero sustainability, the solutions developed herein provide a critical foundation for the future of energy intelligence.

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# Appendices

## A Appendix A: Leveraging Smart Grids and Deep Neural Networks to Achieve Net Zero in the UK: Architecture, Applications, Challenges, and Future Prospects

The United Kingdom (UK) has set an ambitious target to achieve a carbon-neutral economy by 2050, with smart grids and advanced technologies like deep neural networks (DNNs) playing a pivotal role in this transition. Smart grids enable efficient energy management, facilitate the integration of renewable energy sources (RES), and reduce greenhouse gas emissions, while DNNs enhance grid performance by enabling predictive analytics and real-time decision-making. This study provides a thorough examination of the evolution of smart grids in the UK, with a focus on their architecture, applications, and the challenges faced in implementation. We explored the role of DNNs in strengthening smart grid capabilities and advancing carbon neutrality goals. Comparative case studies, such as the Orkney Islands' smart grid and similar projects in Germany and the United States, illustrate the progress and challenges encountered by the UK. The study concludes with recommendations for future development, underscoring the importance of regulatory frameworks, grid resilience, and the integration of advanced technologies.

### A.1 Introduction

The global urgency to combat climate change has led nations to re-evaluate and adjust their energy strategies. The United Kingdom's commitment to achieving net-zero carbon emissions by 2050 is among the most ambitious of these efforts. This target underscores the UK's dedication to environmental stewardship and necessitates a substantial transformation of its energy infrastructure. Central to this shift is the development and deployment of smart grids—advanced electrical systems that leverage digital communication technologies, automation, and data analytics to optimise energy generation, distribution, and consumption. By incorporating higher levels of renewable energy sources (RES), such as wind, solar, and hydro, smart grids are pivotal in facilitating the transition from fossil fuels to a sustainable energy system. The concept of a smart grid goes beyond merely upgrading existing infrastructure; it represents a transformative approach to managing and operating energy systems. Traditional grids were designed for unidirectional energy flow from centralised power plants to end-users. In contrast, smart grids enable bidirectional energy flows, decentralised generation, and real-time communication across grid components. This capability is crucial for integrating distributed energy resources (DERs) such as rooftop solar panels, wind farms, and energy storage solutions. The UK, with its substantial investments in offshore wind and growing interest in solar energy, is particularly well-positioned to benefit from smart grid innovations.

However, the transition to a smart grid poses several challenges. The integration of significant quantities of variable renewable energy into the grid introduces complexities in balancing supply and demand, maintaining grid stability, and ensuring reliable power distribution. Additionally, the increasing digitalisation and automation of grid operations heighten concerns around cybersecurity. Addressing these challenges requires not only technological innovation but also a supportive policy framework and regulatory environment that promotes grid modernisation and encourages investment in advanced technologies.

The integration of artificial intelligence (AI), particularly deep neural networks (DNNs), into smart grid systems marks a significant advancement in the sector. As a branch of machine learning, DNNs have the capability to analyse and interpret vast quantities of data collected in real-time from smart meters, sensors, and various grid components. This functionality enables predictive maintenance, improves the accuracy of demand forecasting, and optimises energy distribution, thereby enhancing the overall efficiency and reliability of the grid. For the United Kingdom, incorporating DNNs within the smart grid framework could greatly accelerate the achievement of net-zero targets by advancing renewable energy management and reducing carbon emissions.

Over the years, the UK's energy system has evolved in response to changing economic, environmental, and technological demands. The enactment of the 2008 Climate Change Act, which set legally binding targets for reducing greenhouse gas emissions, initiated the latest phase of this transition. This Act laid the foundation for subsequent actions and policies aimed at decarbonising the energy sector. A milestone in this journey was the widespread deployment of smart meters, which provided both consumers and grid operators with real-time energy consumption data. This data, vital to the operation of a smart grid, enables more efficient energy management and a smoother integration of renewable energy sources.

The UK has also significantly expanded its renewable energy capacity. Offshore wind, in particular, has become a cornerstone of the UK's renewable energy strategy. By 2024, the UK is home to some of the largest offshore wind farms globally, with capacity expected to grow further in the coming years. Although less prevalent than wind power, solar energy is also gaining traction, especially within residential and commercial sectors. The intermittent nature of these renewable sources, however, presents a challenge to grid stability. Here, AI-driven smart grids equipped with advanced data analytics prove invaluable, as they enable more accurate forecasts of energy generation and consumption, helping to balance supply and demand more effectively.

The development and deployment of energy storage systems (ESS) are also crucial to the UK's energy transition, as these systems address the intermittent nature of renewable sources. ESS can provide essential backup to ensure a stable power supply when conditions are not ideal for wind or solar power. While the UK has invested in various storage technologies, such as pumped hydro storage and lithium-ion batteries, further expansion is necessary to meet future demand. Smart grids play a pivotal role in integrating and managing storage systems, enhancing both grid resilience and reliability.

Demand-side management (DSM) is another key application of smart grids that supports the UK in reaching its net-zero targets. DSM adjusts consumer energy demand through a range of strategies, including demand response programmes, automated load shifting, and time-of-use pricing. By incentivising consumers to reduce or shift their energy use during peak times, DSM reduces grid strain and enables more efficient use of renewable energy. This optimisation of energy consumption patterns not only reduces the need for new power generation but also helps to lower carbon emissions.

Despite their clear benefits, implementing DNNs and smart grids in the UK faces several challenges. A primary concern is ensuring cybersecurity within an increasingly digital and interconnected grid, alongside achieving interoperability across diverse technologies and systems. Additionally, the current regulatory framework may not fully support the rapid deployment of these advanced technologies. Addressing these obstacles will require sustained research and development, coupled with proactive policy reforms.

In summary, the UK's ambition to reach net-zero carbon emissions by 2050 relies significantly on advancements in deep neural networks and smart grid technology. These technologies are central to the UK's energy transition, as they will bolster grid resilience, support the integration of renewable energy sources, and enable more efficient energy management. However, to realise their full potential, technological innovation must be accompanied by enabling legislative frameworks, infrastructure investments, and ongoing research to address the associated challenges. Although achieving net-zero is a demanding goal, with the right policies and strategies, the UK has the opportunity to lead in establishing a resilient and sustainable energy system.

## A.1 Historical Evolution of Smart Grids in the UK

Several factors have driven the development of smart grids in the UK, including the imperative to transition to a low-carbon economy, advancements in technology, and regulatory requirements. The UK's shift towards a smart grid signifies a major transformation in energy production, distribution, and consumption, as well as a leap forward in technological capability. This section examines the historical milestones shaping the evolution of smart grids in the UK, focusing on key legislative actions, scientific breakthroughs, and policy initiatives that have paved the way for the current and future state of the nation's energy infrastructure.

## A.2 Early Beginnings and Legislative Foundations

Concerns over energy security and climate change catalysed the development of the smart grid concept in the UK in the early 2000s. The passing of the 2008 Climate Change Act marked a pivotal moment in UK energy policy, setting legally binding targets to reduce greenhouse gas emissions by at least 80% from 1990 levels by 2050. This landmark legislation, the first of its kind globally, reinforced the UK's commitment to leading efforts in addressing climate change.

Moreover, the 2008 Act laid the groundwork for building a more resilient energy infrastructure capable of integrating a growing proportion of renewable energy sources. This legislative framework inspired subsequent government policies and initiatives focused on modernising the UK's power grid. The emphasis began shifting from a centralised, fossil-fuel-dependent energy system to a more decentralised and sustainable model, embodying the principles essential to smart grids.

## A.3 The Role of Smart Meters in Grid Modernization

The implementations of smart meters across the UK was among the earliest and most significant steps in the development of smart grids. The smart meter programme, running from 2011 to 2020, aimed to equip consumers and energy providers with real-time data on gas and electricity usage. By the end of this initiative, millions of UK households were fitted with smart meters, establishing a foundation for a smarter grid infrastructure.

Smart meters have been instrumental in creating a more efficient, intelligent grid. They provide users with real-time energy monitoring, enabling more informed decisions around energy consumption and often reducing overall demand. For energy companies, the data gathered from smart meters is invaluable for more effective system management, enhancing the efficiency of the energy network, facilitating the integration of renewable sources, and enabling more accurate demand forecasts.

The introduction of smart meters also familiarised consumers with dynamic pricing, where electricity rates vary according to demand and time of day. This has paved the way for more advanced demand-side management (DSM) strategies, which are essential for a fully optimised smart grid.

## A.4 Expansion of Renewable Energy and its Impact on the Grid

Alongside the deployment of smart meters, the UK experienced a significant surge in renewable energy generation. Driven by the government's commitment to reducing carbon emissions and its support for renewable initiatives, the capacity of wind, solar, and other renewable energy sources expanded rapidly.

In particular, the UK has become a global leader in offshore wind energy over the past decade. Projects such as the Hornsea One wind farm, currently the world's largest offshore wind installation, highlight the UK's commitment to scaling up renewable capacity. By 2024, offshore wind is projected to comprise a significant portion of the UK's energy mix, underscoring the need for a smart grid. Given the variability of weather-dependent renewable sources like wind and solar, real-time energy grid management is essential to ensure consistent energy supply.

The rise in renewable energy within the UK's energy mix has also spurred the need for energy storage systems (ESS). ESS are designed to capture surplus energy during periods of high generation and release it during low production or high demand. Integrating ESS into the smart grid is critical for maintaining grid stability and reliability, especially as the UK moves closer to its net-zero targets.

## A.5 Technological Advancements and Pilot Projects

The emergence of smart grids in the UK has also been propelled by significant technological advancements and the rollout of various pilot projects aimed at testing and demonstrating smart grid technologies. A key initiative in this regard was the Low Carbon Networks Fund (LCNF), established by Ofgem, the UK's energy regulator, to promote smart grid technology development.

The LCNF funded numerous pilot projects across the UK, focusing on integrating renewable energy sources, enhancing grid reliability, and improving energy efficiency. These projects played a crucial role in demonstrating the viability of smart grid technologies and provided valuable insights that have guided the broader implementation of smart grids across the country.

Another notable initiative is the Energy Systems Catapult programme, designed to accelerate the transformation of the UK's energy sector. The Catapult has undertaken multiple projects that integrate renewable energy sources, demand-side management, and energy storage systems with smart grid technologies. These efforts have significantly shaped the UK's approach to smart grid development, while also helping to identify and address key challenges in the widespread deployment of smart grids.

## A.6 Policy Initiatives and Strategic Frameworks

The UK government has launched several policy initiatives and strategic frameworks to support the development of smart grids, recognising their importance in achieving net-zero targets. The Smart Systems and Flexibility Plan, published in 2017 and updated in 2021, outlines the government's vision for a smart and flexible energy system. The strategy highlights the need for innovation to facilitate the integration of renewable energy sources, demand-side response (DSR), and energy storage.

The Energy White Paper (2020) further details the government's strategy for transforming the UK energy sector. It underscores the role of smart grids in facilitating the transition to a net-zero economy and identifies necessary actions to modernise the grid, including increasing investments in smart technologies, developing new market frameworks for integrating distributed energy resources (DERs), and enhancing expenditure on grid infrastructure.

The UK's approach to smart grid development is also shaped by its commitment to international agreements such as the Paris Agreement, which calls for global efforts to combat climate change. By taking a pioneering role in climate policy, the UK has positioned itself as a leader in the advancement and implementation of smart grid technology, setting a benchmark for other nations to follow.

## A.7 The Path Ahead: Challenges and Opportunities

As the UK advances its smart grid capabilities, it faces several challenges and opportunities. One of the primary obstacles is ensuring interoperability among the various technologies and systems within the smart grid. To fully harness the potential of emerging technologies, seamless integration with existing grid infrastructure is essential as these innovations are developed and implemented.

Cybersecurity poses another significant challenge, particularly as the grid becomes increasingly digitalised, which introduces new vulnerabilities. Ensuring the smart grid's security and resilience against cyberattacks is crucial for maintaining the reliability of the energy supply.

Conversely, numerous opportunities arise as smart grid technology continues to evolve. Integrating advanced technologies such as artificial intelligence (AI) and machine learning has the potential to further enhance the grid's efficiency and reliability. Additionally, the development of energy storage technologies and the continued expansion of renewable energy sources will be vital for achieving the UK's net-zero ambitions.

In conclusion, the UK's historical evolution of smart grids reflects the country's commitment to establishing a robust and sustainable energy system. Significant progress has been made in modernising the energy infrastructure, beginning with the legislative framework set by the 2008 Climate Change Act and advancing through subsequent technological developments and policy initiatives. As the UK approaches its net-zero emissions targets, smart grids will remain at the forefront of this transition, laying the foundation for a cleaner, more efficient, and sustainable energy future.

## A.8 Smart Grid Architecture in the UK

The smart grid architecture in the UK represents a complex and sophisticated integration of advanced technologies aimed at enhancing the effectiveness, reliability, and sustainability of the nation's energy system. As the UK approaches its goal of achieving net-zero carbon emissions by 2050, the functionality and design of its smart grid architecture are becoming increasingly critical. This section provides a comprehensive analysis of the key components of smart grid architecture in the UK, focusing on generation and distributed energy resources (DERs), transmission and distribution networks, and energy management systems.

### A.8.1 Generation and Distributed Energy Resources (DERs)

The integration of several energy generation sources, with a focus on renewable energy, is central to the UK's smart grid architecture. The United Kingdom has made noteworthy progress in augmenting its renewable energy capability, predominantly via wind and solar power. The UK's transition to a low-carbon energy system is primarily being supported by the growing integration of these renewable energy sources into the grid.

**Offshore Wind Energy:** Many large-scale wind farms are operating off the UK's coastlines, making it a global leader in offshore wind energy. Renewable energy policy in the UK has been synonymous with offshore wind farms, like Hornsea One and Dogger Bank. These initiatives offer a consistent and sizable supply of renewable energy, making a major contribution to the energy blend. Handling wind power variability requires intricate coordination when integrating offshore wind into the smart grid architecture. A steady supply of energy is ensured by predicting wind patterns and modifying energy production in response, using sophisticated forecasting tools and real-time monitoring systems.

**Solar Photovoltaics (PV):** Solar power is essential, especially in the household and commercial sectors, even though the UK has less solar capacity than wind resources. A vital part of distributed energy resources (DERs) are solar photovoltaic (PV) systems, which are frequently mounted on roofs. By producing power at the point of use, these devices lower transmission losses and raise the grid's overall efficiency. These small-scale generation units are integrated into the smart grid design through the use of technologies like grid-tie systems and inverters, which enable the smooth integration of solar electricity into the larger grid.

**Energy Storage Systems (ESS):** Intermittent renewable energy sources provide a significant obstacle to grid integration because they are only available during daylight hours and wind power varies with the weather. In response, the United Kingdom has made investments in a range of energy storage technologies, such as pumped hydro storage and lithium-ion batteries. In times of low output or high demand, these systems release the excess energy they have stored during high production periods. Smart grid architecture ensures grid stability and dependability by balancing the energy flow between generation, storage, and consumption using sophisticated control systems that oversee energy storage and consumption (ESS).

**Electric Vehicles (EVs) and Vehicle-to-Grid (V2G) Technology:** The growing number of electric vehicles in the United Kingdom has potential advantages and difficulties for the intelligent grid. The grid is burdened more when EVs require more electricity to charge, but EVs that have vehicle-to-grid (V2G) technology can function as mobile storage units, resupplying the grid with electricity during times of high demand. To integrate EVs into the larger energy ecosystem, the smart grid architecture must support the bidirectional flow of electricity between EVs and the grid.

**Decentralized Energy Resources:** The UK's smart grid architecture supports decentralised energy resources like microgrids and community energy projects in addition to large-scale renewable energy initiatives. These solutions are especially crucial in isolated or rural locations where the dependability of traditional grid infrastructure may be compromised. By enabling localised power generation and lowering reliance on long-distance transmission lines, decentralised energy resources improve the grid's resiliency.

### A.8.2 Transmission and Distribution Networks

The transmission and distribution networks serve as the fundamental building blocks of the UK's smart grid architecture, facilitating the effective distribution of power from producers to consumers. In order to meet the dynamic demands of a modern energy system and integrate renewable energy, these networks have undergone major upgrades. The proposed smart grid transmission and distribution network in the UK is showing in Figure ***A-1*** and Figure ***A-2***

**High-Voltage Transmission Lines:** Large-scale generation sites, including offshore wind farms, must send their electricity across vast distances to distribution networks that service nearby communities via the UK's high-voltage transmission network. Technologies like high-voltage direct current (HVDC) systems, which are especially useful for sending power over long distances with low losses, have improved the transmission network. For distant offshore wind farms to be connected to the mainland grid, HVDC systems are essential.

**Flexible AC Transmission Systems (FACTS):** In order to regulate the flow of energy inside the transmission network, Flexible AC Transmission Systems (FACTS) have been introduced in the United Kingdom. By controlling voltage levels, directing power flows, and lowering the possibility of grid disruptions, these systems increase the controllability and stability of the grid. To improve the efficiency and dependability of the transmission network, FACTS devices are inserted into it, such as series capacitors and static VAR compensators.

**Smart Substations:** In order to step down high-voltage power to lower voltages appropriate for distribution to homes and businesses, substations are essential nodes in the transmission and distribution networks. Substations have been updated with cutting-edge automation, communication, and sensor technologies as part of the smart grid architecture. Real-time monitoring and control of these "smart" substations enables grid managers to promptly adapt to variations in demand, identify problems, and maximise the flow of electricity across the network.

**Distribution Networks:** Energy is transported from substations to end consumers via the distribution network. Digital technology have improved distribution networks in the UK's smart grid architecture, allowing for improved automation, control, and monitoring. Smart meters are commonly used in the UK. They offer real-time data on power consumption, which helps with load control, demand response programs, and more accurate billing. Distribution network operators (DNOs) utilise this data to make sure that supply and demand are met effectively and to optimise the flow of electricity.

**Wide Area Monitoring Systems (WAMS):** Wide Area Monitoring Systems (WAMS) have been used in the UK to ensure the stability of the entire grid. Phasor measuring units (PMUs) are used by these systems to gather real-time data on the grid's electrical properties, including voltage, current, and frequency. WAMS gives grid operators a thorough understanding of the system's performance, enabling them to promptly identify and address disruptions, avert blackouts, and enhance system performance.

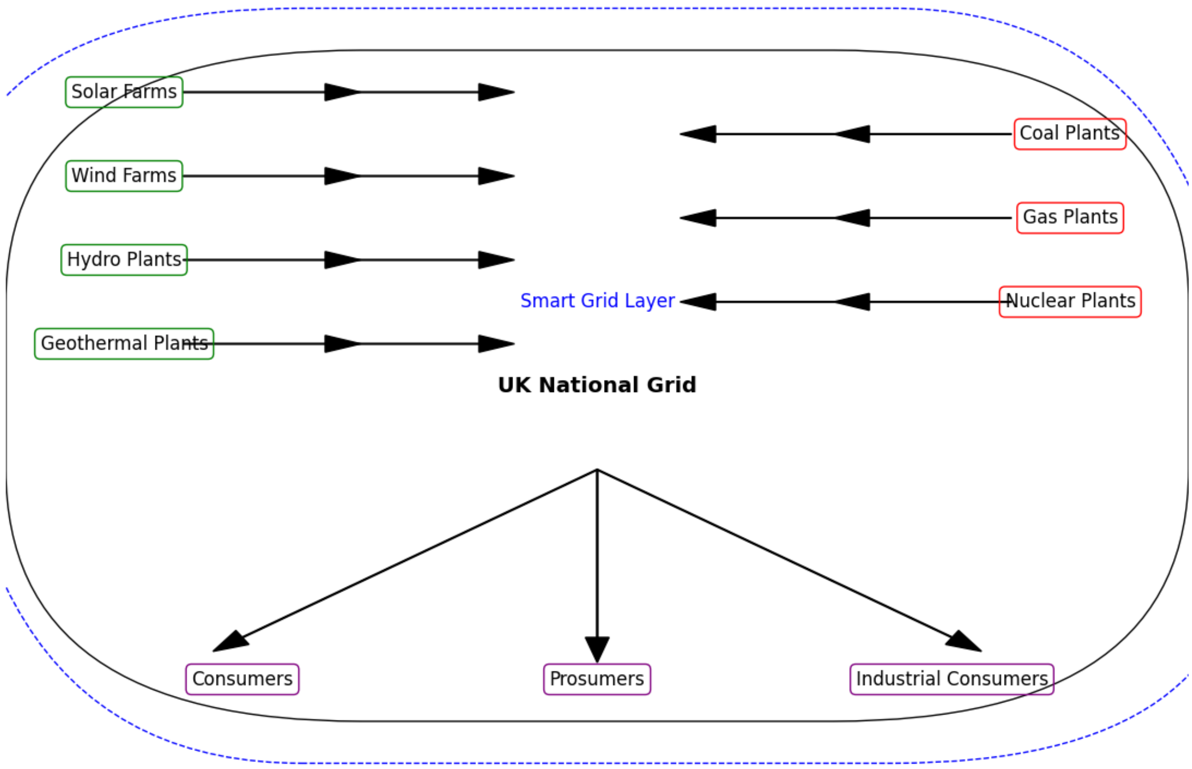


Figure A-1: Smart Grid transmission and distribution network structure

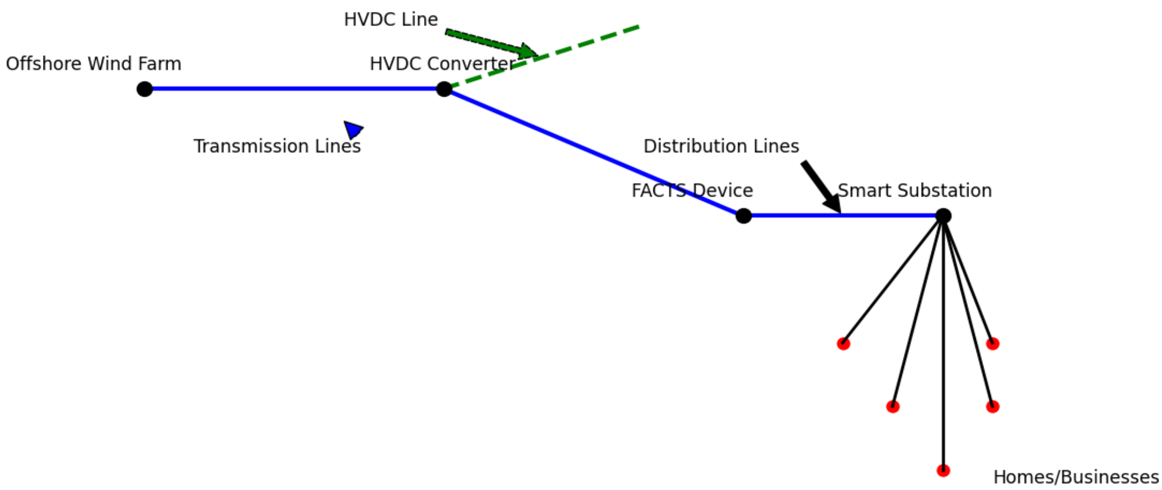


Figure A-2:Proposed UK Smart Grid transmission and distribution network structure

### A.8.3 Energy Management Systems (EMS)

At the core of the smart grid lies the Energy Management Systems (EMS), which play a pivotal role in overseeing the generation, distribution, and consumption of electricity.

In the UK, energy management systems (EMS) are essential for maintaining grid efficiency, integrating renewable energy sources, and balancing supply and demand. The Impact on demand side energy management on daily load curve is showing in Figure *A-3*

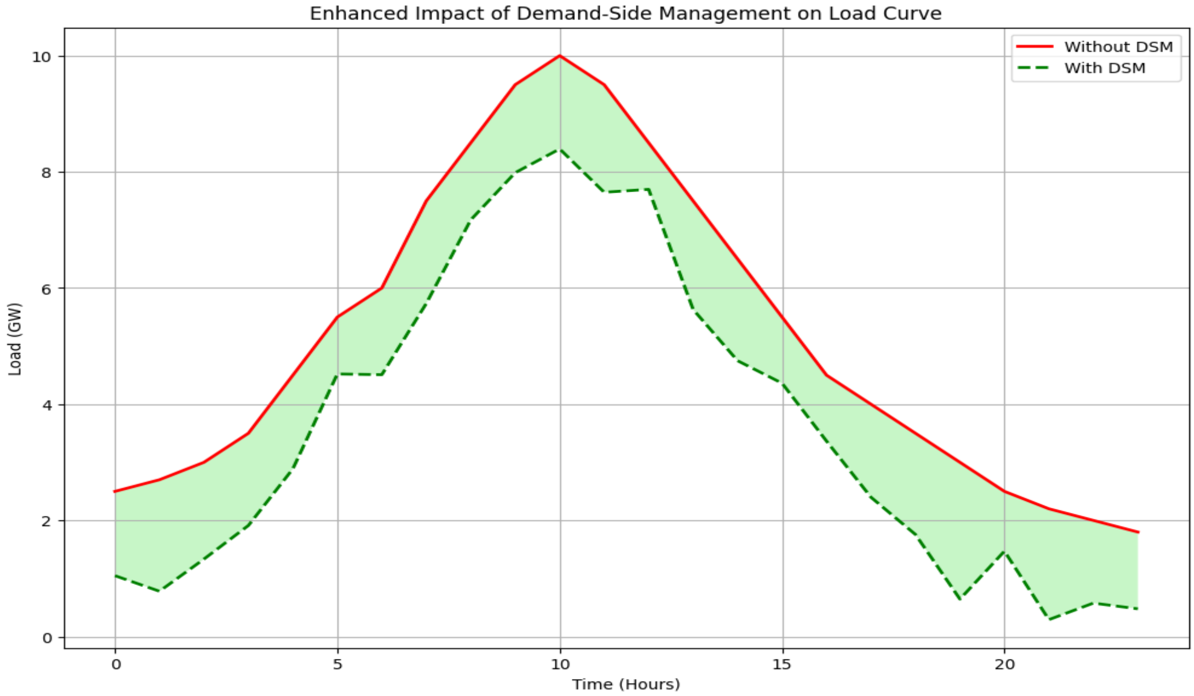


Figure A-3: Impact on demand side energy management on daily load curve

**Demand-Side Management (DSM):** Demand-side management (DSM), which entails modifying customer demand to meet the availability of electricity, is a crucial component of EMS. DSM tactics include demand response programs, which provide incentives for customers to cut back on or alter their energy use during peak hours, and time-of-use tariffs, which set different electricity rates based on the time of day. EMS optimises energy use and lessens grid load by using DSM methods using real-time data from smart meters and other sensors.

**Artificial Intelligence and Machine Learning:** The management of the grid has been completely transformed by the incorporation of machine learning (ML) and artificial intelligence (AI) into EMS. In order to forecast demand patterns, optimise energy dispatch, and identify any defects before they arise, artificial intelligence (AI) programs examine enormous volumes of grid data. AI-driven energy management systems (EMS) are utilised in the UK to improve grid efficiency overall, manage the intermittent nature of solar and wind power, and better the integration of renewable energy sources.

**Real-Time Monitoring and Control:** Grid operators can react quickly to variations in demand, generation, and grid conditions because to EMS's real-time monitoring and control capabilities. In particular, in a system with a large penetration of variable renewable energy sources, this real-time capability is critical to preserving grid stability. To maintain grid balance, EMS can automatically modify generation levels, release energy from storage systems, and apply DSM techniques.

**Microgrids and Local Energy Systems:** In the UK, microgrids and local energy systems are becoming more and more frequent, and EMS are essential to their management. Microgrids are more compact, localised grids that can function both separately and in tandem with the main grid. The management of microgrids is centralised in EMS, which guarantees balanced local generation and consumption as well as smooth transitions between islanded and grid-connected modes.

**Cybersecurity:** The grid is becoming more digitalised, which raises the danger of hackers. EMS is in charge of protecting the digital infrastructure of the grid against cyber-attacks, illegal access, and data breaches by putting cybersecurity measures in place. Because EMS are essential to the functioning of the smart grid, protecting their cybersecurity is a major responsibility in the United Kingdom.

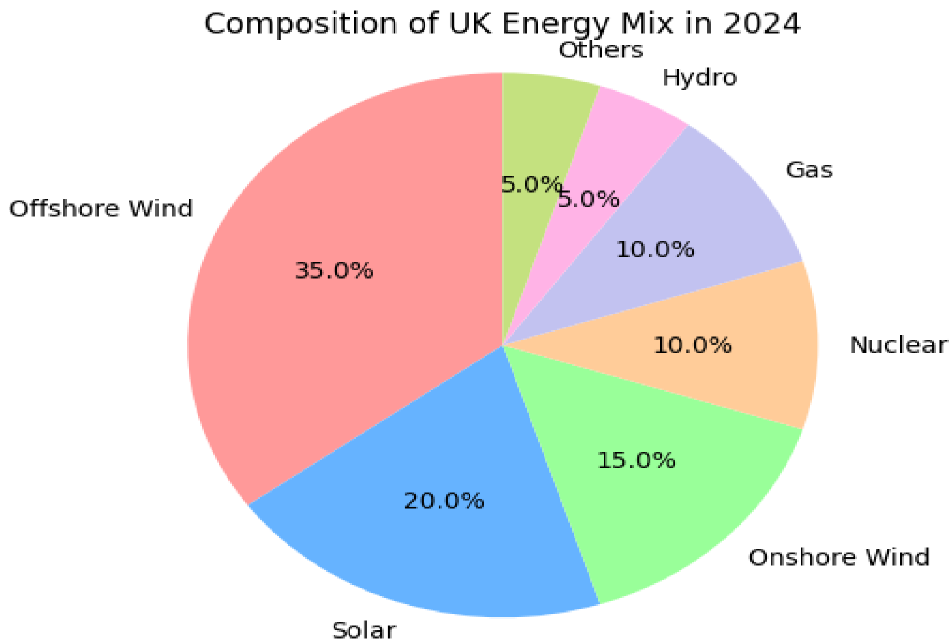


Figure A-4: Composition of UK Energy Mix in 2024

According to the UK department of business, energy and industrial strategy (https://www.gov.uk/government/statistics/energy-consumption-in-the-uk-2022) the comparison of UK energy generation sources are showing in Figure A-4, and the technologies which are implemented in UK transmission and distribution network are showing in Table A-1. The general structure of energy management in UK is showing in Figure A-5.

Table A-1: Key Technologies in UK Transmission and Distribution Networks

| **Technology** | **Functionality** | **Benefits** |
|---|---|---|
| Wide Area Monitoring Systems (WAMS) | Real-time grid monitoring across large areas | Improved grid reliability |
| Flexible AC Transmission Systems | Dynamic control of power flows | Enhanced grid stability |
| Smart Substations | Advanced monitoring and control capabilities | Increased operational efficiency |
| High-Voltage Direct Current (HVDC) | Efficient long-distance power transmission | Reduced transmission losses |

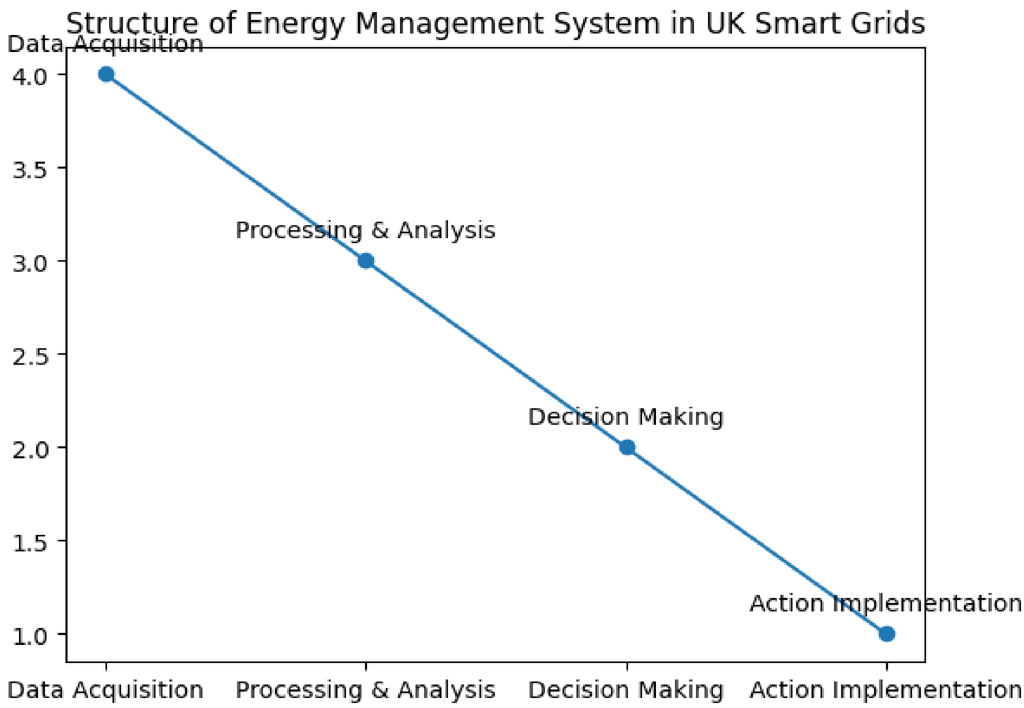


Figure A-5: Structure of Energy Management System in UK Smart Grids

## A.9 Role of Deep Neural Networks in Smart Grids

Smart grid capabilities have advanced significantly with the introduction of deep neural networks (DNNs). DNNs can improve the decision-making process in energy management by processing enormous volumes of data from smart meters, grid sensors, and other sources. This section looks at how DNNs are used in the UK smart grid.

### A.9.1 Predictive Maintenance and Fault Detection

Proactive maintenance is made possible by DNNs' ability to anticipate possible equipment breakdowns before they happen. This increases the longevity of grid infrastructure and decreases downtime. The workflow of data implementation and it's prediction is showing in Figure ***A-6***.

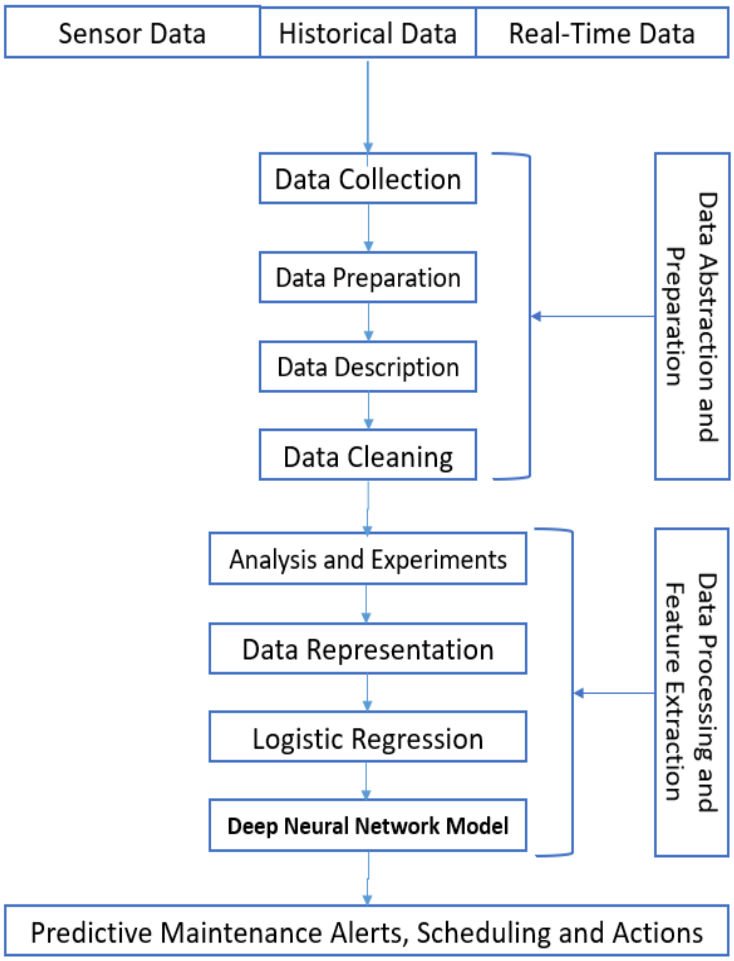


Figure A-6: Predictive Maintenance Workflow Using DNNs

### A.9.2 Demand Forecasting and Load Balancing

DNNs can estimate energy demand with accuracy by examining weather patterns, past usage data, and other variables. This lessens the demand for extra generation capacity and enables grid operators to balance load more effectively. In Table **A-2**, there is the comparison of DNN, time series and regression model algorithms in perspective of mean absolute percentage error, and it's shows that DNN is the best one to deal with large and diverse datasets.

Table A-2: Accuracy of Demand Forecasting Techniques

| **Technique** | **Mean Absolute Percentage Error (MAPE)** | **Data Requirements** |
|---|---|---|
| Time Series Analysis | 5-10% | Historical consumption data |
| Regression Models | 4-8% | Consumption, weather data |
| Deep Neural Networks | 2-5% | Large datasets, diverse data |

### 4.3 Renewable Energy Integration

DNNs can improve the efficiency of renewable integration into the grid by optimising the dispatch of renewable energy sources. This is especially critical for controlling the erratic nature of solar and wind energy. The renewable energy integration in electrical systems to optimise the overall system is showing in Figure A-7.

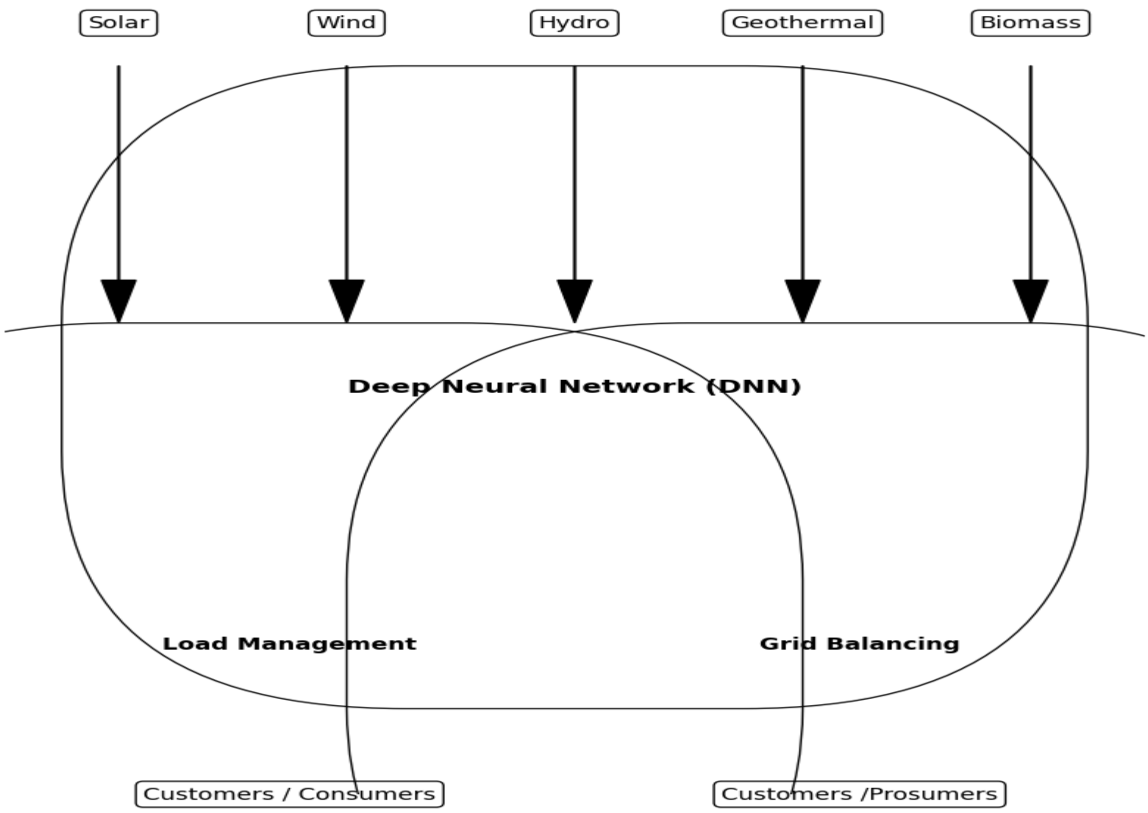


*Figure A-7: Renewable Energy Integration Optimisation Using DNNs*

## A.10 Applications of Smart Grids in Achieving Net Zero

The UK's plan to attain net-zero emissions by 2050 heavily relies on smart grid technology. The particular uses of smart grids that advance this objective are examined in this section.

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### A.10.1 Renewable Energy Integration

Smart grids are primarily used for the integration of renewable energy sources. Carbon emissions and dependency on fossil fuels are declining in the UK as offshore wind and solar electricity become more widely integrated into the system as shown in Table **A-3**, from 2015-2024.

Table A-3: Impact of Renewable Energy Integration on Carbon Emissions

| **Year** | **Renewable Energy Share (%)** | **Carbon Emissions Reduction (%)** |
|---|---|---|
| 2015 | 25 | 10 |

| Year | Renewable Energy Share (%) | Carbon Emissions Reduction (%) |
|---|---|---|
| 2020 | 40 | 25 |
| 2024 | 55 | 40 |

### A.10.2 Energy Storage Systems (ESS)

The intermittent nature of renewable energy sources necessitates the use of energy storage devices. To improve grid stability, the UK has made investments in several storage technologies, such as pumped hydro storage and lithium-ion batteries as shown in Figure ***A-8***.

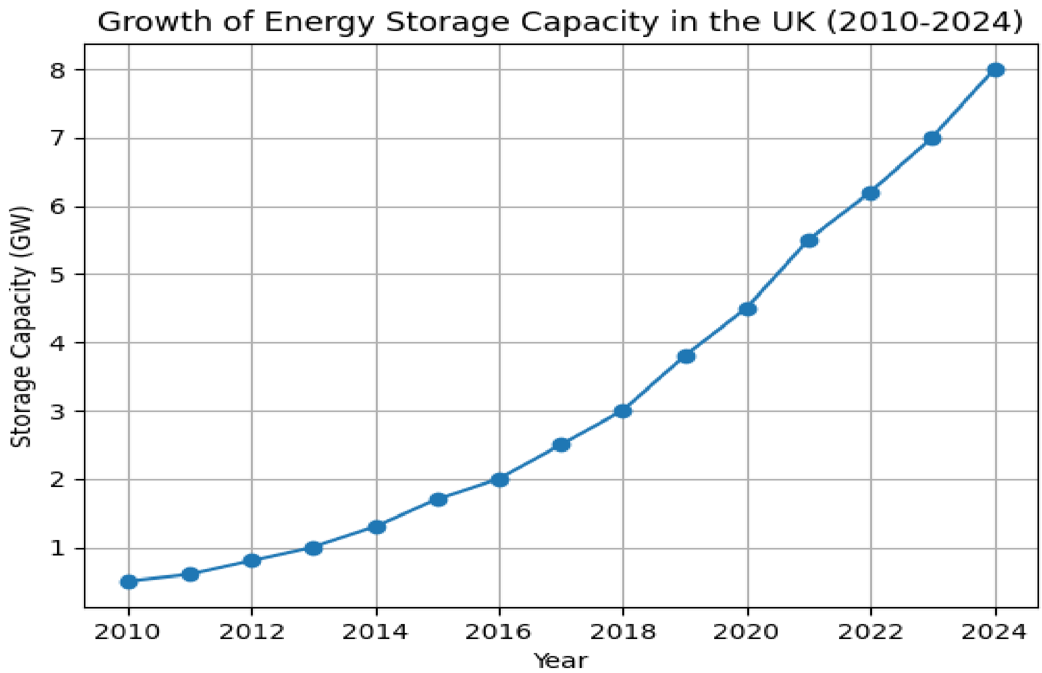


Figure A-8: Growth of Energy Storage Capacity in the UK (2010-2024)

### A.10.3 Demand-Side Management (DSM)

Demand-side management strategies, such automated load shifting and time-of-use charges, assist in balancing energy use during peak hours. As a result, the system is less stressed and renewable energy may be used more effectively. The impact of DSEM on peak load reduction is showing in Figure A-9.

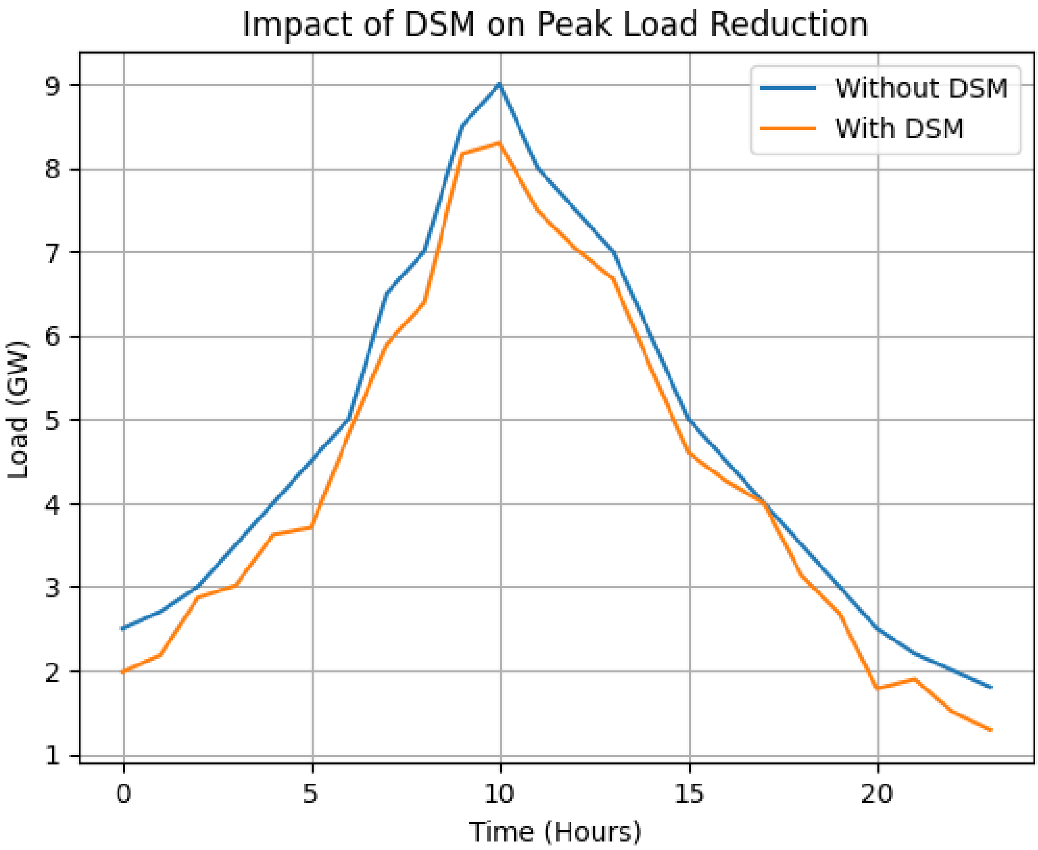


Figure A-9: Impact of DSM on Peak Load Reduction

## A.11 Challenges in the Deployment of Smart Grids and DNNs

Although smart grids and DNNs have many advantages, their effective implementation in the UK will depend on addressing a number of issues.

### A.11.1 Interoperability

Compatibility problems may arise when multiple technologies from different vendors are integrated. For the smart grid to function effectively, communication and collaboration between all of its parts must be guaranteed as shown in Table ***A-4***.

Table A-4: Interoperability Challenges in Smart Grid Deployment

| Challenge | Description | Potential Solutions |
|---|---|---|
| Vendor-Specific Protocols | Different communication protocols used by vendors | Development of standardized protocols |
| Legacy Systems Compatibility | Integrating new technologies with existing infrastructure | Gradual upgrading and retrofitting of legacy systems |
| Data Integration | Merging data from various sources into a unified system | Implementation of data standardization frameworks |

### A.11.2 Cybersecurity

Smart grids' greater reliance on digital communication and control technologies makes them more susceptible to hackers. It is essential to defend the grid against these attacks in order to guarantee the security and dependability of the energy supply as shown in Figure **A-10**.

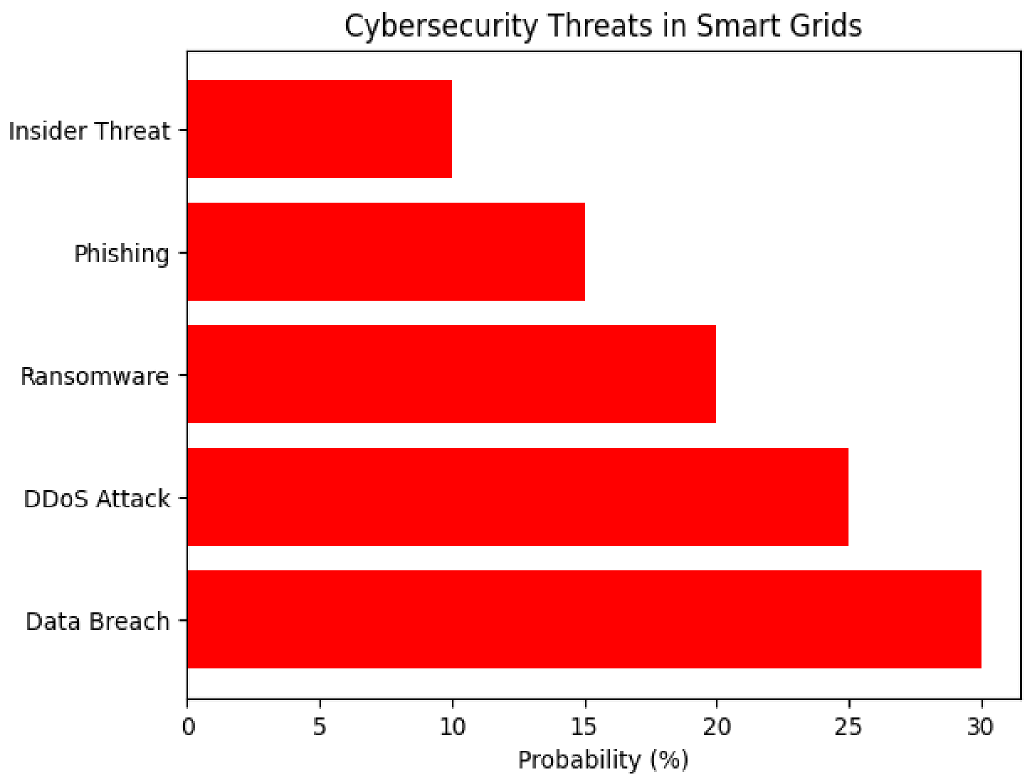


Figure A-10: Cybersecurity Threats in Smart Grids

### A.11.3 Regulatory Barriers

The dynamic nature of smart grids may require modifications to the current regulatory frameworks, especially about energy market rules and grid management as shown in Table **A-5**.

Table A-5: Regulatory Challenges and Recommendations

| **Regulatory Challenge** | **Description** | **Recommendations** |
|---|---|---|
| Market Structure Limitations | Current market structures may not support DERs integration | Reform energy markets to include DER participation |
| Policy Uncertainty | Lack of clear policies for smart grid deployment | Establish long-term, clear policies for grid modernization |
| Grid Code Updates | Existing grid codes may not reflect new technologies | Regularly update grid codes to include emerging technologies |

## A.12 Case Studies

Three case studies that demonstrate the use of DNNs with smart grids to accomplish net-zero objectives are presented in this section. These case studies shed light on the difficulties and achievements associated with implementing smart grids in various situations.

### A.12.1 Case Study 1: Smart Grid Implementation in the UK - Achieving Net-Zero through Renewable Energy Integration

The United Kingdom has been at the forefront of the global transition to a low-carbon economy. Given the ambitious target of achieving net-zero greenhouse gas emissions by 2050, integrating renewable energy sources into the national grid is essential. A crucial aspect of this transition is the UK's smart grid programme, which facilitates the more effective management of renewable energy resources, reduces reliance on fossil fuels, and enhances grid resilience. Over the past decade, the landscape of power generation in the UK has undergone a remarkable transformation, with renewable energy sources such as wind, solar, and hydropower gradually replacing traditional coal- and gas-fired power plants. By 2020, renewable sources accounted for over 40% of the electricity generated in the UK, with offshore wind playing a pivotal role. The challenge now lies in managing the intermittent output of these renewable energy sources while ensuring grid stability and meeting electricity demand.

**Smart Grid Technology Implementation**

The smart grid program in the UK aims to tackle the difficulties associated with incorporating renewable energy sources into the grid. Important technologies consist of the following:

1. **Advanced Metering Infrastructure (AMI):**

   Advanced Metering Infrastructure (AMI) involves the deployment of smart meters in residential and commercial settings. These meters provide real-time information on energy consumption, enabling users to manage their energy usage more effectively. Additionally, the data collected from smart meters is utilised by grid operators to optimise energy distribution and reduce peak demand.

2. **Demand Response Programs:**

   Demand response initiatives are designed to incentivise consumers to reduce or shift their electricity usage during times of peak demand. By offering financial rewards, these programmes help balance supply and demand while minimising the reliance on fossil fuel-powered peaking plants. In the UK, such initiatives have been particularly effective in managing the variability associated with wind energy generation.

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3. **Energy Storage Systems:**

   The UK has made investments in sizable battery storage systems that are designed to store extra energy produced by renewable sources during off-peak hours. When demand is high or renewable generation is low, these systems can release stored energy. Maintaining grid stability has been shown to need battery storage, especially during times when solar and wind output fluctuate.

4. **Grid Automation and Control Systems:**

   Modern grid automation technologies have been implemented to improve the UK's electrical grid's dependability and effectiveness. These systems monitor grid performance and automatically modify power flows to prevent outages using real-time data from sensors and meters. Automation is necessary since the complexity of managing the grid has increased with the integration of renewable energy sources.

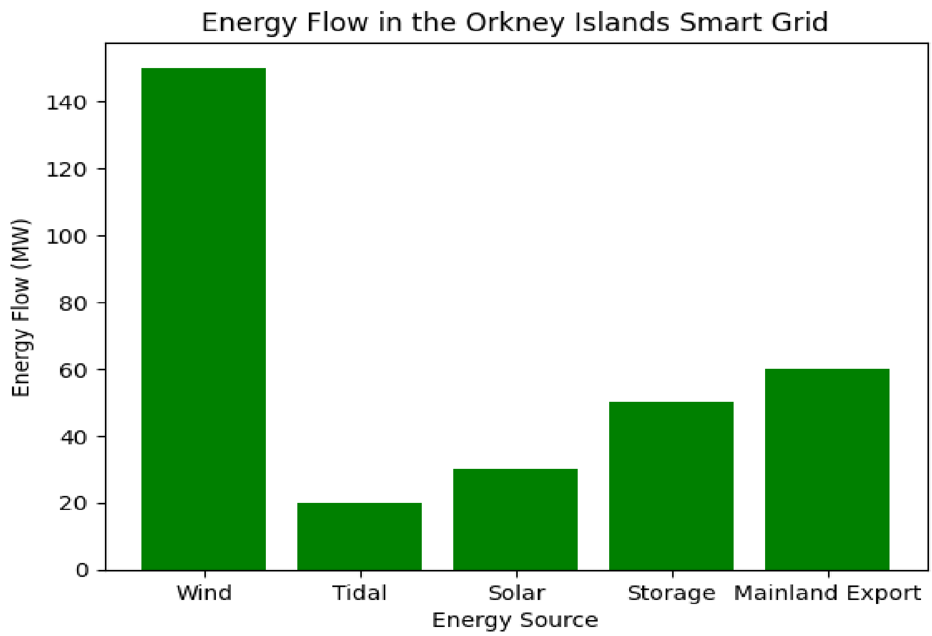


Figure A-11: Energy Flow in the Orkney Islands Smart Grid

**Impact on Net-Zero Goals**

The UK's ability to incorporate renewable energy into the grid and move closer to its net-zero targets has been significantly impacted by the deployment of smart grid technologies. Among the principal results are:

- **Increased Renewable Energy Penetration:** The UK has been able to raise the proportion of renewable energy in its energy mix thanks to the smart grid. Carbon emissions have significantly decreased as a result of the integration of solar and wind power, which has decreased dependency on fossil fuels.

- **Enhanced Grid Resilience:** The energy grid in the United Kingdom is now more resilient thanks to the installation of energy storage devices and grid automation. These innovations have made it possible for the grid to adjust to variations in the production of renewable energy, lowering the possibility of blackouts and guaranteeing a steady supply of power.

- **Empowered Consumers:** Customers are now able to manage their energy use thanks to smart metering and demand response programs. This has helped create a more efficient and balanced grid in addition to lowering overall energy use.
- **Reduction in Peak Demand:** Demand may now be shifted away from peak times, which eliminates the need for peaking plants that use on fossil fuels and significantly lowers greenhouse gas emissions.

**Challenges and Lessons Learned**

Despite the success of the UK's smart grid initiative, several challenges remain:

- **Intermittency of Renewable Energy:** Grid operators still have difficulties because of the unpredictability of solar and wind energy. Further innovation in storage technology is required, even if energy storage devices have helped to reduce this issue.
- **Infrastructure Investment:** A large infrastructure investment is needed to make the switch to a smart grid, including smart meters, sensors, and communication networks. For policymakers, ensuring that this investment yields value for money is a top priority.
- **Consumer Engagement:** Despite the effectiveness of demand response systems, more customer involvement is still required. Maximising the impact of smart grid technology requires educating customers about their advantages and motivating them to participate in demand response initiatives.

The United Kingdom's smart grid effort has been essential in the nation's shift to a low-carbon economy. The smart grid has significantly aided in the UK's efforts to achieve net-zero emissions by facilitating the integration of renewable energy sources, improving grid resilience, and empowering customers. To overcome the remaining obstacles and guarantee the long-term success of the transition to a sustainable energy future, however, further innovation and investment in grid infrastructure will be necessary.

### A.12.2 Case Study 2: California's Renewable Energy Integration - The Role of Smart Grids in Achieving Net-Zero

California, the most populous state in the United States, has established some of the nation's most ambitious climate goals, aiming for net-zero greenhouse gas emissions by 2045. At the forefront of smart grid technology development and renewable energy deployment, California's initiatives have significantly advanced the state's progress toward these targets.

Historically, California has been a leader in environmental legislation, prioritising the adoption of renewable energy and reducing carbon emissions. The state's Renewable Portfolio Standard (RPS) mandates that utilities source 60% of their electricity from renewable sources by 2030, with a long-term goal of achieving 100% carbon-free electricity by 2045. By 2020, approximately 34% of California's electricity generation came from renewable sources, predominantly solar and wind energy.

However, integrating these variable renewable energy sources into the electrical grid while maintaining affordability and reliability has posed significant challenges. In response, California has leveraged its smart grid initiatives as a primary tool to address these issues.

**Smart Grid Technology Implementation**

In order to make it easier to integrate renewable energy, California has concentrated its smart grid development efforts in a few important areas:

1. **Advanced Distribution Management Systems (ADMS):**

   ADMS software platforms allow utilities to better manage the distribution network. In order to guarantee that power is delivered throughout the grid in a reliable and efficient manner, ADMS are utilised in California to monitor and regulate the flow of electricity from renewable sources.

2. **Microgrids:**

   Microgrids are localised grids that may function independently of the main grid, and California has been a leader in their deployment. Resilience against grid disruptions and support for the state's decarbonisation objectives are two benefits of microgrids, which frequently combine energy storage and renewable energy sources. Microgrids have proven to be especially helpful in wildfire-prone areas for sustaining power during crises.

3. **Energy Storage:**

California has made significant investments in energy storage devices, notably lithium-ion batteries, to handle the intermittent nature of solar and wind power. When demand is high or renewable generation is low, these systems release the excess energy they have stored during times of high renewable output. The 300 MW Moss Landing Energy Storage Facility, the biggest battery storage facility in the state, is an essential part of the state's renewable energy plan.

4. **Demand Response and Dynamic Pricing:**

Demand response programs, which California has put in place, encourage users to use less electricity during peak hours. In order to encourage off-peak usage, dynamic pricing has been implemented, which modifies the cost of power dependent on demand. These steps lessen the need for fossil fuel-based power plants and assist to balance the grid.

5. **Grid Modernization and Resilience:**

To increase the resilience of the electrical system, the state has also made investments in grid modernisation projects. To improve grid operations, this entails modernising transmission lines, putting sophisticated sensors in place, and putting real-time data analytics into practice. Managing the growing complexity of a system that mostly depends on distributed renewable energy sources will need these efforts.

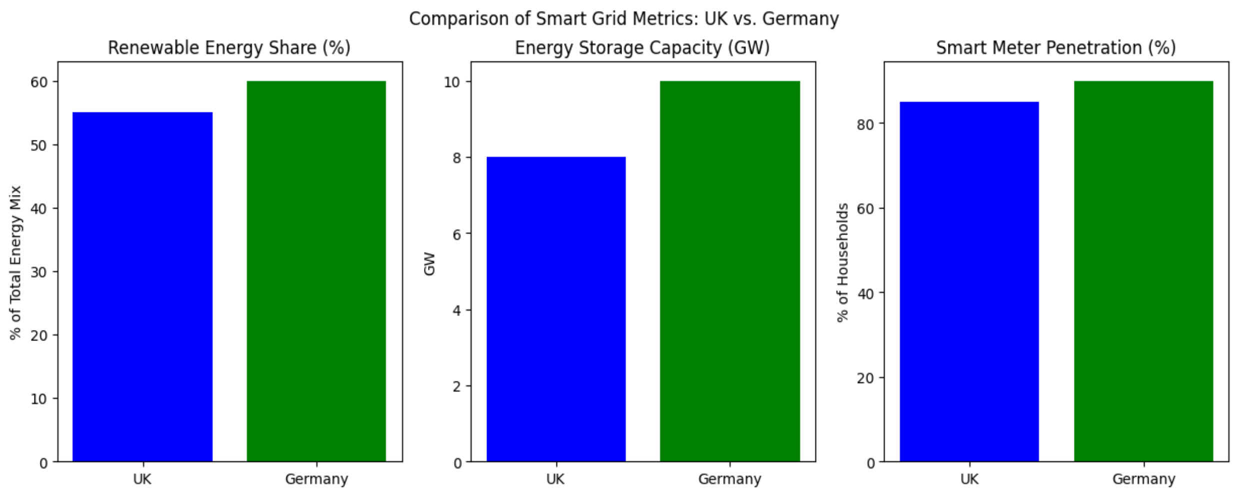


Figure A-12: Comparison of Smart Grid Metrics: UK vs. Germany

Table A-6: Comparison of Smart Grid Metrics: UK vs. Germany

| Metric | UK | Germany |
|---|---|---|
| Renewable Energy Share (%) | 55 | 60 |
| Energy Storage Capacity (GW) | 8.0 | 10.0 |
| Decentralization Level | Moderate | High |
| Smart Meter Penetration (%) | 85 | 90 |

**Impact on Net-Zero Goals**

California's progress towards reaching its net-zero emissions objective has been significantly impacted by its smart grid efforts:

- **Renewable Energy Integration:** Large-scale renewable energy integration into the grid has been made possible in California by the implementation of smart grid technologies. Thanks to energy storage and demand response initiatives, the state's infrastructure can now handle times when renewable supply outpaces demand.
- **Grid Stability and Resilience:** The stability and resilience of the grid in California have been improved through the deployment of ADMS, microgrids, and energy storage. These innovations have been especially crucial in controlling the state's increasing reliance on solar energy, which can cause abrupt changes in the availability of electricity.
- **Consumer Participation:** In California, demand response programs and dynamic pricing have been effective in getting customers to take responsibility for their electricity use. This has lessened grid stress during times of high demand and helped to lower peak demand.
- **Reduction in Carbon Emissions:** California has decreased carbon emissions from the electrical sector significantly by decreasing its reliance on fossil fuel-based power plants and increasing the amount of renewable energy in the energy mix. In keeping with its overall climate goals, the state's greenhouse gas emissions have been continuously declining.

**Challenges and Lessons Learned**

Despite the success of California’s smart grid initiatives, several challenges remain:

- **Wildfire Risks:** The electrical system is seriously at risk from the number and intensity of wildfires that are occurring more frequently in California. Even if grid modernisation and microgrids have increased resilience, more money needs to be spent on fire prevention and mitigation techniques.
- **Cost and Affordability:** The integration of renewable energy sources and the shift to a smart grid necessitate large financial investments. Policymakers' top priority is to make sure that low-income customers are not disproportionately affected by the expenses of these expenditures.
- **Managing Intermittency:** Although the intermittent nature of renewable energy has been mitigated by energy storage technologies, additional research and development is required to create more scalable and affordable storage options. Managing times of high demand and low renewable generation will also require increasing the use of demand response and dynamic pricing.

The state of California has made significant strides in reaching its net-zero emissions goal thanks to its smart grid efforts. Reduction in carbon emissions and increase in the proportion of renewable energy in the state's energy mix can be attributed to the integration of renewable energy sources, improved system resilience, and active consumer participation. continual issues like the cost of modernising the system and the possibility of wildfires, however, emphasise the necessity of continual innovation and investment in smart grid technologies. The smart grid will continue to be a vital part of California's plan for a sustainable energy future as the state pursues its aggressive climate targets.

### A.12.3 Case Study 3: Germany’s Energiewende (Energy Turnaround) - The Role of Smart Grids in the Energy Transition

One of the most thorough and ambitious attempts to decarbonise an industrialised economy is Germany's Evergreened, or energy transformation. The project seeks to lower dependency on fossil fuels, phase out nuclear energy, and raise the proportion of renewable energy in the energy mix. In order to successfully integrate renewable energy sources, maintain grid stability, and help Germany reach its target of net-zero greenhouse gas emissions by 2045, smart grid technologies must be developed and put into use. Energy security, climate change, and the intention to phase out nuclear power after the Fukushima accident in 2011 all played major roles in Germany's energy transition, which got underway in earnest in the early 2000s. The nation established lofty goals to boost energy efficiency, increase the production of renewable energy, and decrease greenhouse gas emissions.

Wind and solar energy were Germany's main suppliers of renewable energy, contributing about 46% of the country's electricity generation by 2020. The development of smart grid solutions was necessary, nevertheless, as the quick growth of renewable energy sources presented serious problems to the stability and dependability of the electrical infrastructure.

**Smart Grid Technology Implementation**

Germany has concentrated its smart grid development efforts on a few key areas to help the Evergreened succeed and integrate renewable energy:

1. **Decentralized Energy Generation and Grid Integration:**

   Decentralisation of energy generation, together with a notable rise in distributed renewable energy sources like rooftop solar panels and small-scale wind turbines, has been a defining feature of Germany's energy transition. To ensure that power is distributed effectively and consistently, smart grids have proved crucial in regulating the integration of these decentralised sources into the national grid.

2. **Flexible Power Systems:**

   The need for adaptable power systems that can react fast to shifts in supply and demand derives from the unpredictability of wind and solar power. Germany has made investments in smart grid technology that provide real-time grid monitoring and control, enabling quick modifications to power flows and guaranteeing the stability of the system.

3. **Energy Storage and Sector Coupling:**

   Germany has made investments in a variety of energy storage technologies, such as battery storage, pumped hydro, and power-to-gas, to handle the intermittent nature of renewable energy. Because these storage devices are part of the smart grid, extra renewable energy may be saved and used later on. One important tactic for balancing supply and demand has been sector coupling, which entails connecting the electrical grid with other energy sectors like transportation and heating.

4. **Demand-Side Management and Smart Meters:**

Demand-side management initiatives have been put in place in Germany to encourage customers to switch their electricity use to times when there is less demand. The installation of smart meters has been essential in giving customers access to real-time data on their electricity usage, allowing them to take part in demand response programs and optimise their energy use. Additionally, smart meters give grid operators useful information for better grid management.

5. **Grid Modernization and Digitalization:**

Digitalisation and grid modernisation are major investments made as part of Germany's smart grid initiative. In order to optimise grid operations, this entails modernising the grid's physical infrastructure, putting in place cutting-edge sensors and communication networks, and applying machine learning and data analytics. The creation of virtual power plants, which combine dispersed energy resources to offer grid services, has also been made possible by digitalisation.

**Impact on Net-Zero Goals**

Germany's progress towards reaching its net-zero emissions objective has been greatly impacted by the adoption of smart grid technologies:

- **Increased Renewable Energy Integration:** Germany has been able to incorporate significant volumes of renewable energy into the grid even as the percentage of decentralised generation has increased thanks to smart grids. As a result, the nation's dependency on fossil fuels has decreased, and the power industry's greenhouse gas emissions have decreased.

- **Enhanced Grid Stability and Resilience:** The German electrical grid has become more resilient and stable with the introduction of sector coupling, energy storage technologies, and flexible power systems. These technological advancements have been essential in controlling the unpredictability of renewable energy sources and guaranteeing a steady flow of electricity.

- **Consumer Participation and Energy Efficiency:** Demand-side management initiatives and the installation of smart meters have given consumers more control over how much energy they use, which has enhanced energy efficiency and decreased demand overall. This has assisted in bringing the system into balance and lowering carbon emissions.

- **Support for the Energy Transition:** An important factor in the Energiewende (Energy Transition) and the nation's shift to a low-carbon economy has been Germany's smart grid effort. The viability of attaining a large share of renewables while preserving grid stability and reliability has been proved by the successful integration of renewable energy sources into the grid.

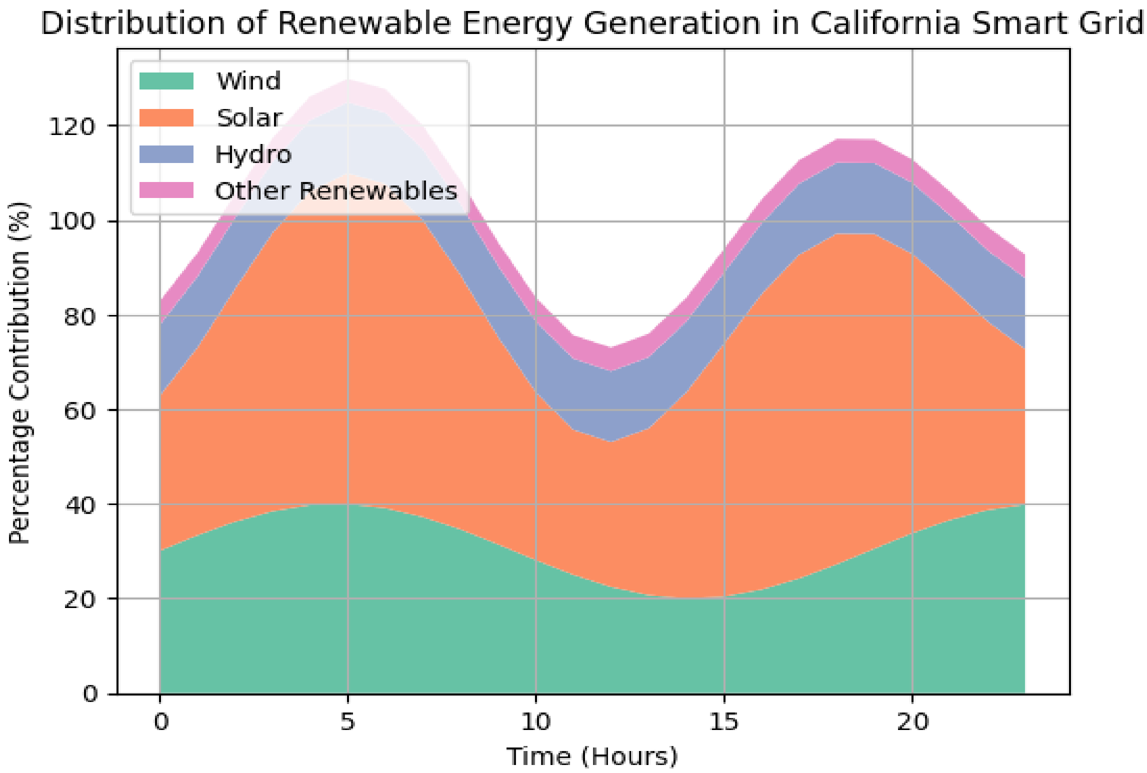


Figure A-13: Distribution of Renewable Energy Generation in California Smart Grid

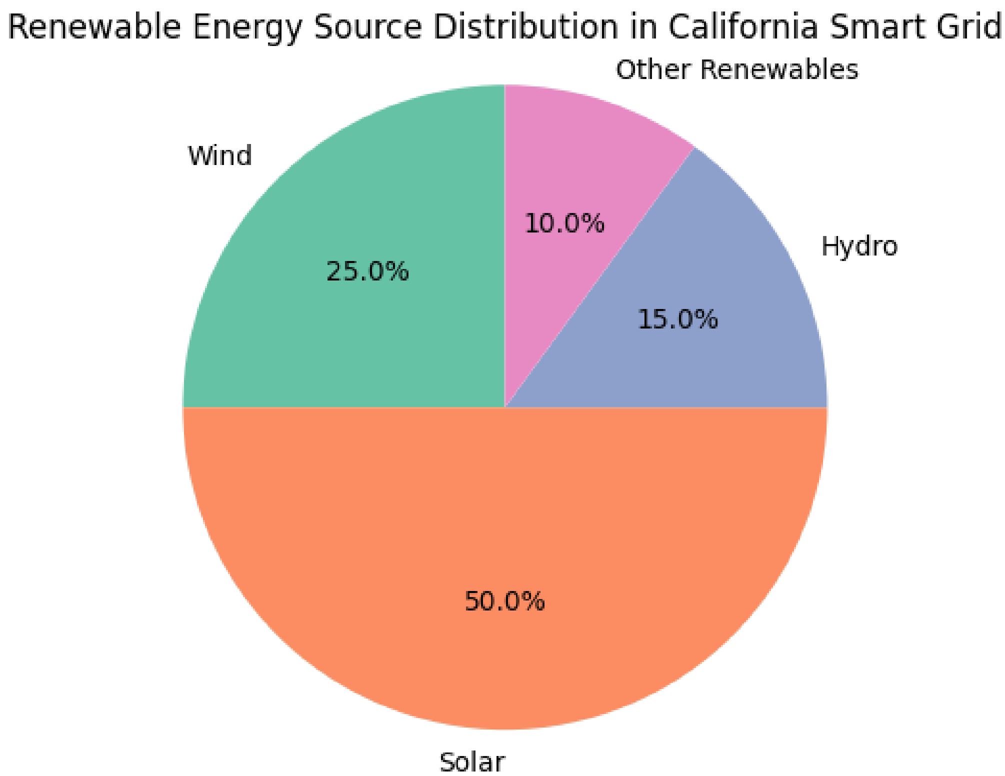


Figure A-14: Distribution of Renewable Energy Generation in California Smart Grid

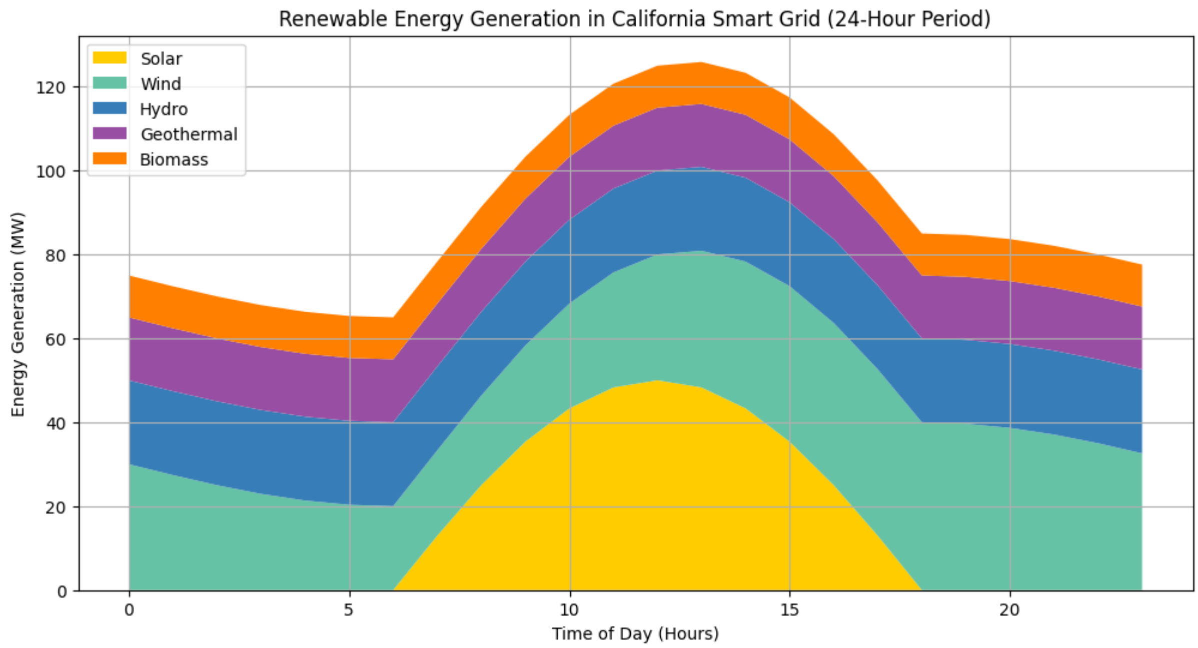


Figure A-15: Renewable Energy Generation in California Smart Grid

**Challenges and Lessons Learned**

Despite the success of Germany's smart grid initiatives, several challenges remain:

- **Grid Congestion and Infrastructure Investment:** In certain areas of Germany, especially in the north where wind power generation is abundant, the fast growth of renewable energy has resulted in system congestion. This has made it clear that more money needs to be invested in the grid's infrastructure in order to move power from high-generation areas to high-demand places.
- **Public Acceptance and Social Equity:** Social equality and public acceptability have become issues with the deployment of smart grid technologies and the switch to renewable energy sources. A major issue facing legislators is making sure that the expenses of the energy transition are allocated equitably and that every customer has access to reasonably priced electricity.
- **Cybersecurity and Data Privacy:** The digitisation of the electrical grid has led to concerns regarding data privacy and an increase in the risk of cyberattacks. Maintaining the integrity of the grid and the confidence of the public depends on ensuring the security and privacy of the data gathered by smart meters and other grid technology.

Germany has made significant progress towards reaching its net-zero emissions target and the Energiewende (Energy Transition) thanks to its smart grid efforts. Reducing carbon emissions and increasing the proportion of renewable energy in the energy mix have been made possible by the integration of renewable energy sources, the creation of flexible power systems, the installation of smart meters, and demand-side management initiatives. But persistent issues like cybersecurity, public acceptability, and grid congestion emphasise the necessity of continual research and development into smart grid systems. Germany will continue to rely heavily on the smart grid as part of its vision for a sustainable energy future as it works towards its aggressive climate targets.

These three case studies illustrate various facets of renewable energy integration and smart grid deployment in Germany, the UK, and California. Although each region has its own set of difficulties, by using cutting-edge technologies and creative strategies, they are all far closer to achieving their net-zero objectives.

The three case studies on smart grid deployment and renewable energy integration in the UK, California, and Germany are summarised in the comparison table below:

Table A-7: Smart Grid case studies comparison in UK, California and Germany

| **Aspect** | **UK Smart Grid** | **California Smart Grid** | **Germany's Energiewende (Energy Turnaround or Energy Transition)** |
|---|---|---|---|
| **Primary Goal** | Achieving net-zero by 2050 through renewable integration and grid modernization | Achieving net-zero by 2045 with a focus on renewable energy and grid resilience | Transition to a low-carbon economy by 2045 through the Energiewende initiative |
| **Key Renewable Energy Sources** | Offshore wind, solar, hydro | Solar, wind, battery storage | Wind (onshore and offshore), solar, biomass |
| **Smart Grid Technologies** | Advanced Metering Infrastructure (AMI), Demand Response, Energy Storage, Grid Automation | Advanced Distribution Management Systems (ADMS), Microgrids, Energy Storage, Dynamic Pricing | Decentralized generation, Flexible Power Systems, Energy Storage, Sector Coupling, Digitalization |
| **Energy Storage Solutions** | Large-scale battery systems for balancing wind and solar | Lithium-ion batteries, large-scale storage facilities like Moss Landing | Battery storage, pumped hydro, power-to-gas technologies |
| **Consumer Engagement** | Demand response programs, smart metering | Demand response, dynamic pricing | Smart meters, demand-side management |
| **Grid Resilience** | Enhanced through energy storage and automation | Strengthened by microgrids and grid modernization | Supported by flexible power systems and sector coupling |

| Aspect | UK Smart Grid | California Smart Grid | Germany's Energiewende (Energy Turnaround or Energy Transition) |
|---|---|---|---|
| **Challenges** | Intermittency of renewable energy, infrastructure investment, consumer engagement | Wildfire risks, cost and affordability, managing intermittency | Grid congestion, public acceptance, cybersecurity |
| **Impact on Carbon Emissions** | Significant reduction due to increased renewable penetration and reduced peak demand | Steady decline in emissions through renewable integration and reduced reliance on fossil fuels | Significant reductions in emissions, high share of renewables in the energy mix |
| **Technology Innovations** | Smart grid automation, real-time data analytics, large-scale energy storage | Microgrids, large-scale battery storage, ADMS, dynamic pricing | Digitalization, virtual power plants, advanced storage solutions |
| **Public and Policy Support** | Strong government support for net-zero initiatives, regulatory frameworks in place | State-led initiatives, strong policy framework for renewable energy | Strong public and policy support for Energiewende, focus on sustainability |
| **Lessons Learned** | Importance of consumer engagement, need for ongoing innovation in storage technologies | Critical role of resilience in grid management, importance of dynamic pricing and consumer participation | Need for continued investment in grid infrastructure, importance of public acceptance and cybersecurity |

| Aspect | UK Smart Grid | California Smart Grid | Germany's Energiewende (Energy Turnaround or Energy Transition) |
| --- | --- | --- | --- |
| **Overall Progress** | On track to achieve net-zero by 2050 with strong focus on renewable integration and smart grid technology | Significant progress towards net-zero by 2045, leading in renewable energy deployment and grid modernization | High renewable energy penetration, strong progress in energy transition, ongoing challenges with grid modernization |

**Summary of the Comparison:**

- **Renewable Energy Sources:** The UK is primarily dependent on offshore wind, but California invests extensively in battery storage and concentrates on solar and wind energy. With significant contributions from both onshore and offshore wind, Germany has a varied mix.
- **Smart Grid Technologies:** Despite having different priorities, all three regions have adopted cutting edge smart grid technologies. Demand response and storage are prioritised in the UK and California, whilst decentralisation and digitisation are led by Germany.
- **Challenges:** Although every area has its own set of difficulties, they are all related to the intermittent nature of renewable energy sources, the requirement for infrastructure spending, and public acceptance. Germany concentrates on cybersecurity and grid congestion management, whereas California deals with the possibility of wildfires as well.
- **Impact on Carbon Emissions:** Significant success in cutting carbon emissions is demonstrated in all three case studies, mostly due to the growing integration of smart grid and renewable energy technology.

- **Consumer Engagement:** Demand response programs and smart metering are important tools for controlling energy use and maintaining grid balance, and consumer participation is essential in all regions.

A brief summary of the parallels and discrepancies between the methods and results of renewable energy integration and smart grid deployment in Germany, the UK, and California is given in this table.

## A.13 Future Scope and Recommendations

Future energy infrastructure development in the UK depends on the effective adoption and ongoing advancement of smart grid technology. In order to meet the UK's target of having net-zero carbon emissions by 2050, there are a number of areas where additional development and strategic attention will be essential. The main directions for smart grid growth in the future are outlined in this part, along with suggestions for making sure the UK's energy infrastructure is secure, robust, and able to meet future demands.

### A.13.1 Expansion of Renewable Energy Integration

Reducing carbon emissions and hitting net-zero goals require the smart grid to incorporate renewable energy sources. The infrastructure that is in place now, however, needs to keep changing to accommodate the growing use of renewable energy, especially offshore wind and solar power. The scope of the future comprises:

- **Enhanced Forecasting and Management**: Real-time management systems and better forecasting models are required due to the unpredictability of renewable energy sources like solar and wind. In order to maximise the integration of renewable energy sources into the grid and anticipate weather patterns with greater accuracy, the UK needs invest in cutting edge AI and machine learning (ML) technology.

- **Grid Modernization and Expansion**: The grid's capability to manage the added demand must expand along with the potential of renewable energy sources. This include building new renewable energy projects' connections to the grid, improving substations, and modernising transmission lines. In order to effectively transfer significant amounts of electricity from offshore wind farms to the mainland, High-Voltage Direct Current (HVDC) lines must be installed.

- **Distributed Energy Resources (DERs) Integration**: Distributed energy resources like community energy initiatives, rooftop solar panels, and nearby wind turbines need to be better supported by future smart grids. The creation of microgrids and local energy networks that can function both independently and in tandem with the national grid is necessary to achieve this. Improved energy management systems and inverter technologies are required to guarantee the seamless integration of these decentralised resources.

### A.13.2 Advanced Energy Storage Solutions

The intermittent nature of renewable energy sources must be addressed, and energy storage is essential. The need for scalable, effective, and affordable energy storage technologies grows as the UK's reliance on renewable energy sources rises. Energy storage's potential in the future includes:

- **Investment in Large-Scale Battery Storage**: The United Kingdom ought to persist in funding extensive lithium-ion battery initiatives while concurrently investigating substitute storage technologies like flow batteries, compressed air energy storage (CAES), and solid-state batteries. These devices ensure a steady supply of energy by storing extra energy produced during times of low demand and releasing it during moments of peak demand.
- **Integration of Vehicle-to-Grid (V2G) Technology**: The UK has a special chance to take use of V2G technology, which allows EVs to feed electricity back into the grid when needed, thanks to the growing popularity of EVs. This improves grid flexibility in addition to offering more storage capacity. It will be essential to implement laws and incentives to promote the use of V2G-capable automobiles and charging infrastructure.
- **Research and Development (R&D) in Long-Duration Storage**: In order to control seasonal changes in the output of renewable energy, long-duration energy storage—which can store energy for days or even weeks—will be essential. The UK should place a high priority on research and development of technologies that can provide the energy system the resilience it needs, such as molten salt batteries, underground pumped hydro storage, and hydrogen storage.

### A.13.3 Enhanced Cybersecurity and Resilience

Cyberattacks are becoming more likely as smart grids become increasingly digitally and globally integrated. Maintaining a dependable energy supply and safeguarding vital infrastructure in the UK requires ensuring the energy infrastructure's resilience and cybersecurity.

- **Development of Robust Cybersecurity Frameworks**: Comprehensive cybersecurity frameworks that address the unique vulnerabilities of smart grids must be developed in the UK. This entails putting in place robust encryption, safe communication procedures, and instantaneous monitoring systems that can promptly identify and address cyberthreats.

- **Resilience Planning and Risk Management**: Resilience planning should be a part of the UK's smart grid's future in order to mitigate risks from both cyber threats and natural disruptions like severe weather. This include building disaster recovery strategies that give priority to power restoration in the case of an outage, ensuring that key infrastructure can function independently in emergencies, and adding redundancy to the grid.

- **International Collaboration**: Because cyber threats are worldwide in scope, the UK ought to work with other nations and international organisations to exchange best practices, threat intelligence, and coordinate responses to cyber-attacks aimed at smart grids.

### A.13.4 Policy and Regulatory Innovation

UK legislative and regulatory frameworks need to be innovative in order to facilitate the ongoing development of smart grids. In addition to guaranteeing that market incentives support decarbonisation and grid modernisation, this will also ensure that new technologies can be integrated effectively.

- **Updating Grid Codes and Standards**: The UK's grid rules and regulations need to be revised to take into account the increasing prevalence of new technologies including AI-driven energy management systems, DERs, and advanced storage options. As part of this, new technical guidelines for cybersecurity, energy efficiency, and grid connectivity will be established.

- **Incentives for Decentralized Energy Production**: The UK government should provide subsidies, tax exemptions, and feed-in tariffs for small-scale renewable energy producers in order to promote the growth of microgrids and decentralised energy generation. These rewards can aid in defraying the upfront investment expenses and promote widespread use.

- **Market Reforms for Flexibility Services**: The energy market in the UK has to be changed to better support flexibility services, which let grid operators adjust supply and demand instantly. In order to incentivise participants to contribute to grid stability, new markets for demand-side response, storage, and other flexibility services must be established.

- **Encouraging Public-Private Partnerships**: The UK energy market has to be restructured to better accommodate flexibility services, which allow grid operators to rapidly alter supply and demand. It is necessary to create new markets for demand-side response, storage, and other flexibility services in order to encourage players to contribute to grid stability.

### A.13.5 Public Engagement and Education

Public participation and education will also be essential to the UK's energy transition's success. Enhancing customers' comprehension and involvement in the energy system is necessary since they play an increasingly crucial role in the operation of smart grids.

- **Consumer Education Programs**: Programs for educating consumers on the advantages of smart grids, renewable energy, and energy efficiency should be funded by the UK. These initiatives can enable users to take part in demand-side management programs and make knowledgeable decisions about how much energy they use.

- **Incentivizing Behavioral Change**: Government programs like time-of-use pricing, which incentivises customers to use energy during off-peak hours, should be taken into consideration as a means of encouraging behavioural change in addition to education. Additionally successful are reward schemes for consuming less energy during peak hours.

- **Community Energy Projects**: Encouraging community energy initiatives gives local communities a direct say in how much energy is produced and used, which can improve public participation. These initiatives can support local economic growth while raising knowledge of sustainability and renewable energy.

Table A-8: Key Recommendations for Future Smart Grid Development in the UK

| Recommendation | Rationale | Expected Outcome |
|---|---|---|
| Expand AI/ML Integration | Enhance grid performance and predictive capabilities | Improved grid reliability and efficiency |
| Increase Energy Storage Deployment | Address intermittency of renewables | Enhanced grid stability |
| Policy and Regulatory Reform | Ensure framework supports modernized grid technologies | Facilitated deployment of smart grid solutions |

## A.14 Discussion and Future Research Directions

As the United Kingdom progresses toward its ambitious objective of achieving net-zero carbon emissions by 2050, transitioning to a smart grid-enabled energy infrastructure is both essential and inevitable. This transformation signifies a significant shift in the methods of energy production, distribution, management, and consumption, transcending mere technological advancements. The integration of renewable energy sources, advanced data analytics, artificial intelligence (AI), and reliable energy storage technologies within the smart grid framework presents an exciting path toward a sustainable and resilient energy future.

However, several challenges and gaps remain that require ongoing research and innovation. The current study concludes by summarizing the key research findings and outlining specific research objectives. It highlights areas needing further investigation to fully realize the potential of smart grids in the United Kingdom.

### A.14.1 Summary of Key Findings

The evolution of smart grid infrastructure in the UK has been shaped by legislative mandates, technological advancements, and the growing imperative to integrate renewable energy sources. The establishment of energy management systems (EMS), the rollout of smart meters, and the increase in renewable energy capacity have laid the groundwork for a more adaptable and intelligent grid. Nonetheless, further efforts are needed to enhance grid security, implement advanced AI-driven technologies, and integrate distributed energy resources (DERs).

The existing smart grid architecture in the UK demonstrates the potential for a decentralized, resilient, and sustainable energy system. By incorporating energy storage systems and leveraging AI and machine learning for demand forecasting, predictive maintenance, and real-time decision-making, the grid can enhance overall efficiency and better manage the variability of renewable energy. However, as the grid becomes more complex, the risks of cyberattacks and system vulnerabilities also increase, highlighting the critical need for robust cybersecurity measures.

### A.14.2 Future Research Directions

Further research is required in a few areas, even though the current body of work offers a solid foundation for the development of smart grids. To solve current issues and improve the UK's smart grid infrastructure, future research should concentrate on the following crucial areas:

### A.14.3 Advanced AI and Machine Learning Integration

The operation of smart grids could be completely transformed by artificial intelligence and machine learning. But much remains to be done to fully realise their promise, especially in the areas of real-time grid management, predictive analytics, and energy flow optimisation. Subsequent investigations must to concentrate on:

- **Developing Advanced Predictive Models**: Improved predictive models are required so that renewable energy production variations can be predicted, demand can be more precisely forecasted, and possible system faults can be identified before they happen. Hybrid AI models that can adjust to the dynamic nature of the grid, deep learning approaches, and reinforcement learning should all be investigated in future research.

- **AI-Driven Optimisation Algorithms**: Artificial Intelligence (AI) can improve the optimisation techniques currently employed in EMS. In the future, studies should focus on creating AI-driven optimisation algorithms that can manage complex, multi-objective optimisation issues like balancing energy production and consumption, cutting expenses, and concurrently lowering carbon emissions.

- **AI in Decentralized Grid Management**: AI has the potential to be extremely important in controlling these dispersed resources as the grid grows increasingly decentralised with more microgrids and distributed energy resources (DERs). To ensure that local energy systems can function independently while still being connected to the national grid, research should concentrate on artificial intelligence approaches that facilitate decentralised decision-making.

### A.14.4 Enhanced Cybersecurity Measures

Significant cybersecurity risks are introduced by the grid's digital revolution, and if these risks are not handled, the stability and dependability of the entire energy system may be compromised. Future studies in this field ought to give priority to:

- **Cybersecurity Frameworks for Smart Grids**: Comprehensive cybersecurity frameworks that are specifically designed to address the risks present in smart grids are desperately needed. Creating frameworks with sophisticated encryption methods, secure communication protocols, and real-time threat detection systems should be the main goal of research.

- **AI for Cybersecurity**: AI can potentially be used to improve smart grid cybersecurity. Research ought to look into the use of AI in real-time cyber threat detection and response, as well as in spotting trends and anomalies that can point to possible security lapses.

- **Resilience Against Cyber-Physical Attacks**: Smart grids introduce new risks due to the integration of physical and cyber components. Future studies should look into methods such as the creation of redundant systems, fail-safe mechanisms, and quick recovery procedures to strengthen the grid's resistance to cyber-physical attacks.

### A.14.5 Energy Storage Innovations

Although present technologies have limitations in terms of cost, efficiency, and scalability, energy storage is essential for controlling the intermittent nature of renewable energy sources. Research ought to concentrate on:

- **Next-Generation Battery Technologies**: Higher energy density, longer lifespans, and cheaper costs are needed in next-generation battery technologies, even though lithium-ion batteries now dominate the market. Alternatives including flow, solid-state, and organic battery technologies should be investigated through research.

- **Long-Duration Energy Storage**: Long-duration energy storage technologies are needed to handle seasonal changes in the production of renewable energy. Future studies should look into cutting-edge energy storage techniques including thermal storage, which may hold energy for weeks or even months, advanced pumped hydro, and hydrogen storage.

- **Integration of Vehicle-to-Grid (V2G) Systems**: V2G systems provide the twin benefits of energy storage and grid flexibility as electric cars (EVs) become more common. In order to address issues with battery deterioration, grid infrastructure, and market mechanisms, research should concentrate on optimising the integration of V2G devices into the grid.

### A.14.6 Policy and Regulatory Frameworks

The establishment of favourable legislative and regulatory frameworks that promote investment, innovation, and customer involvement is also essential to the success of smart grid adoption. Studies in this field should look at:

- **Incentive Structures for DERs and Storage**: Research should examine the creation of efficient incentive systems, such as grants, tax breaks, and performance-based awards, in order to hasten the adoption of DERs and energy storage. Analysing the effects of various incentive models on grid stability and financial viability is part of this.

- **Regulatory Standards for AI and Automation**: Regulations that guarantee the ethical and safe application of AI and automation are necessary as these technologies become more and more integrated into smart grid operations. Creating guidelines for AI accountability, openness, and fairness in decision-making procedures should be the main goal of research.

- **Market Design for Flexibility Services**: New market structures that compensate for services like distributed generation, energy storage, and demand response are required due to the growing demand for grid flexibility. Market mechanisms that can incorporate these services into the current energy markets while maintaining fair competition and consumer protection should be the subject of research.

### A.14.7 Public Engagement and Behavioural Change

The success of smart grids is greatly influenced by consumer behaviour, especially when it comes to demand-side management and energy-saving programs. Studies ought to look into:

- **Behavioural Economics of Energy Consumption**: It is essential to comprehend the variables influencing customer energy behaviour while creating demand-side management strategies. Research ought to look into how behavioural economics might be used to create energy-saving measures including social norm campaigns, energy feedback mechanisms, and time-of-use pricing.

- **Community Energy Models**: Future studies ought to look into the possibilities of community energy models, in which local people actively participate in the production and management of energy. This entails examining the effects community energy initiatives have on society, the economy, and the environment as well as figuring out how best to scale these models.

- **Consumer Trust in Smart Grid Technologies**: Establishing and preserving consumer trust is crucial as smart grid technologies grow more widespread. Research ought to look into ways to boost customer trust in smart grid technologies' security, privacy, and dependability, such as open communication, consumer education, and strong data protection protocols.

Table A-9: Future Research Directions for the UK Smart Grid

| Focus Area | Specific Research Goals | Potential Challenges | Expected Outcomes |
|---|---|---|---|
| **AI and Machine Learning Integration** | - Develop advanced predictive models for renewable energy forecasting.<br>- Create AI-driven optimisation algorithms for energy management.<br>- Implement AI for decentralized grid management. | - Data availability and quality.<br>- High computational requirements.<br>- Integration with legacy systems. | - Improved accuracy in energy forecasting.<br>- Enhanced grid efficiency and reliability.<br>- Autonomous operation of local energy systems. |
| **Cybersecurity Measures** | - Design comprehensive cybersecurity frameworks tailored for smart grids.<br>- Utilize AI for real-time threat detection and response.<br>- Enhance resilience against cyber-physical attacks. | - Rapidly evolving threat landscape.<br>- High costs of implementing advanced security measures.<br>- Ensuring user privacy. | - Increased security and resilience of the smart grid.<br>- Reduced risk of cyberattacks.<br>- Enhanced trust in smart grid systems. |
| **Energy Storage Innovations** | - Explore next-generation battery technologies (e.g., solid-state, flow batteries).<br>- Research long-duration energy storage | - High development and deployment costs.<br>- Technical challenges with new | - Greater grid stability and flexibility.<br>- Cost-effective and scalable energy storage options.<br>- Increased adoption of V2G technologies. |

| Focus Area | Specific Research Goals | Potential Challenges | Expected Outcomes |
|---|---|---|---|
| | solutions.<br>- Optimise vehicle-to-grid (V2G) system integration. | materials.<br>- Regulatory barriers for V2G. | |
| **Policy and Regulatory Frameworks** | - Develop incentive structures for DERs and energy storage.<br>- Establish regulatory standards for AI and automation in the grid.<br>- Design markets for flexibility services. | - Balancing innovation with consumer protection.<br>- Regulatory inertia.<br>- Ensuring fair market competition. | - Accelerated adoption of smart grid technologies.<br>- Fair and transparent market operations.<br>- Increased grid flexibility and resilience. |
| **Public Engagement and Behavioural Change** | - Investigate behavioural economics for demand-side management.<br>- Study the impacts of community energy models.<br>- Enhance consumer trust in smart grid technologies. | - Public resistance to change.<br>- Communication challenges.<br>- Data privacy concerns. | - Increased consumer participation in energy management.<br>- Empowered local communities in energy production.<br>- Higher adoption rates of smart grid technologies. |

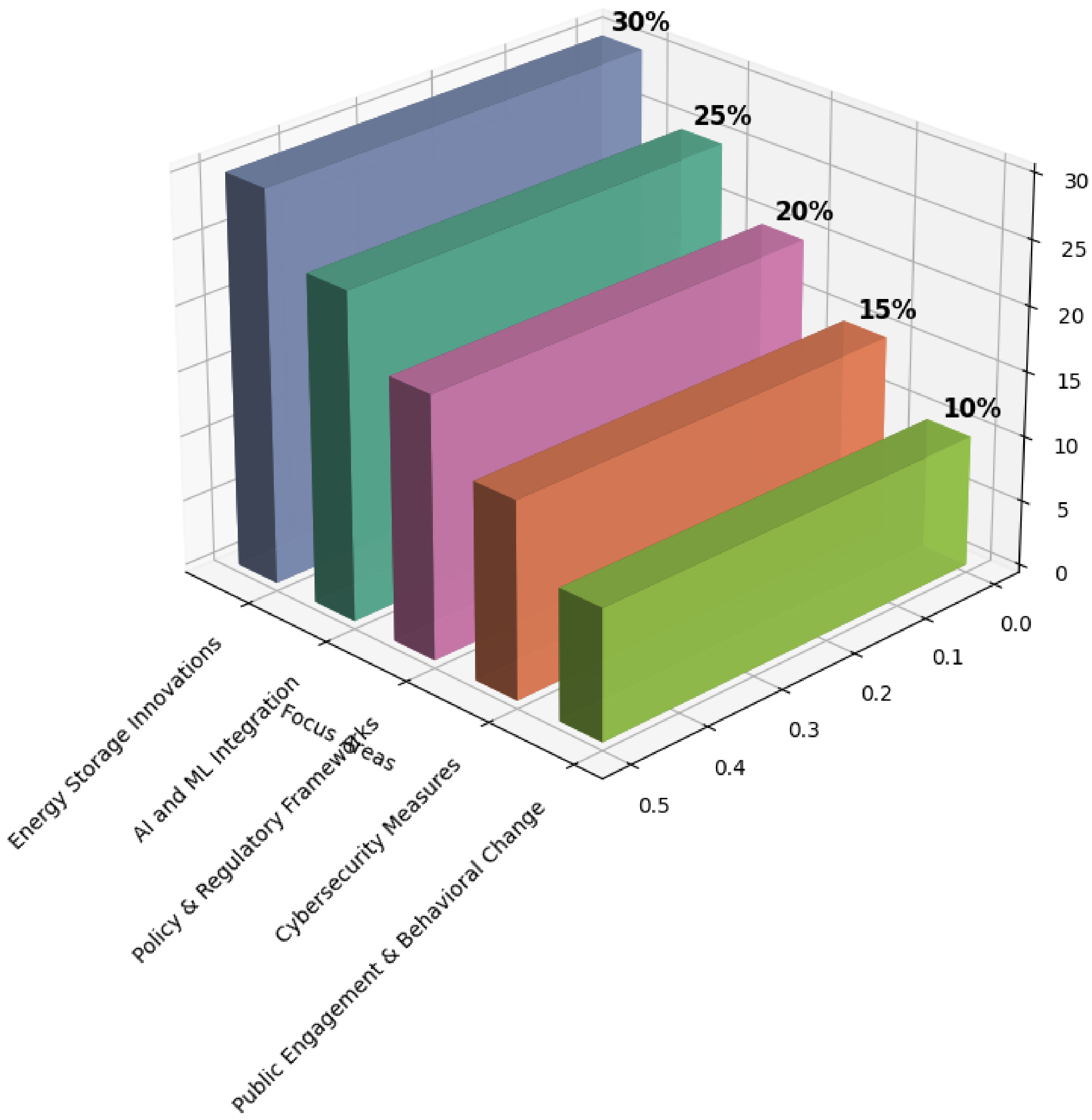


Figure A-16: Future directions to work on several aspects to achieve net zero

## A.15 Summary of Chapter

To meet its ambitious target of achieving net-zero carbon emissions by 2050, the UK must transition to an energy system supported by smart grid technology. This study outlines the key components, challenges, and future directions required to transform the existing grid into a more resilient, efficient, and sustainable smart grid. It is essential to integrate advanced energy storage solutions, renewable energy sources, and AI-driven energy management systems. These technological advancements, combined with robust cybersecurity measures and innovative regulatory frameworks, will ensure the reliability and security of the electricity system. The UK's leadership in offshore wind energy, commitment to expanding solar capacity, and the increasing adoption of electric vehicles further support these smart grid technologies. However, the challenge lies in effectively integrating these various elements into a cohesive, efficient, and secure grid, highlighting the need for further research and development, particularly in areas such as decentralized energy management, long-duration energy storage, and AI optimisation.

The successful implementation of a smart grid in the UK relies on continuous technological and policy advancements, along with proactive public engagement. The role of consumers in this transition cannot be overstated; as active participants in distributed energy generation and demand-side management, they will be crucial in balancing supply and demand. Additionally, the government's ability to create policies that incentivize innovation while ensuring fairness and accessibility for all segments of society will be pivotal in driving the energy transition. This study underscores the importance of a multidisciplinary approach that merges data science, policy analysis, engineering, and social sciences to address the various challenges associated with implementing smart grids. By focusing on these areas, the UK can achieve its net-zero goals while promoting economic growth and energy security, setting a global example for creating a sustainable, secure, and equitable energy future.