FAULT DETECTION IN ELECTRICAL POWER TRANSMISSION SYSTEMS USING ARTIFICIAL NEURAL NETWORK ALGORITHMS

A Thesis Submitted to the

Department of Systems Engineering

INSTITUTE OF SPACE SCIENCE AND ENGINEERING

An Affiliate of

AFRICAN UNIVERSITY OF SCIENCE AND TECHNOLOGY

In Partial Fulfilment of the Requirements for the Degree of

MASTER OF SCIENCE

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FEBRUARY 2024

DEDICATION

I dedicate this project to God Almighty for His grace and Favour which saw me through my Master’s programme.

CERTIFICATION

This is to certify that the thesis titled **FAULT DETECTION IN ELECTRICAL POWER TRANSMISSION SYSTEMS USING ARTIFICIAL NEURAL NETWORK ALGORITHMS**, submitted to the school of postgraduate studies, African University of Science and Technology (AUST), Abuja, Nigeria for the award of a Master's degree, is a record of an original research carried out by **TEMPLE OLOTU ABBOTT** in the **SYSTEMS ENGINEERING DEPARTMENT** of the Institute of Space Science and Engineering (ISSE), an affiliate of AUST.

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A THESIS APPROVED BY THE DEPARTMENT OF SYSTEMS ENGINEERING

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ACKNOWLEDGMENT

I thank God for His Grace and favour which saw me through my master's programme.

I also thank my wife Mrs. Ruth Abbott for her love, understanding, patience, and support all through my Master's programme. My thanks also go to my lovely Mother for her words of encouragement, support, and love all through this Master's programme.

Finally, I thank Prof. Azikiwe Peter Onwualu, the President of the African University of Science and Technology (AUST) for his teachings, encouragement, and wise words of advice throughout this programme. I also thank Dr. Ale Felix and the entire team at the National Space Research and Development Agency (NASRDA) for the exposure and knowledge gained through this programme.

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ABSTRACT

The reliability and stability of electrical power transmission systems are critical for ensuring uninterrupted power supply. Fault detection in these systems is a significant challenge due to the complexity and dynamic nature of the electrical grid. This thesis presents a novel approach for fault detection in electrical power transmission systems using an Artificial Neural Network (ANN) algorithms. The proposed method leverages the pattern recognition capabilities of ANNs to accurately identify and classify various types of faults, including Voltage and Frequency anomalies. By analyzing these anomalies at one end of the transmission line, the ANN model is trained to detect anomalies and predict fault conditions with high precision. The performance of the ANN-based fault detection system is evaluated and validated through extensive simulations in the MATLAB environment, demonstrating its effectiveness in real-time fault detection and classification. The results indicate that the ANN algorithm not only enhances the speed and accuracy of fault detection but also reduces the risk of power outages and equipment damage. This research contributes to the development of more resilient and intelligent Power Transmission Systems, paving the way for future advancements in Smart Grid technologies.

Keywords: Artificial Intelligence (AI), Artificial Neural Networks (ANN), Power Transmission Systems, MATLAB, Smart Grid Technologies.

CHAPTER ONE

INTRODUCTION

1.1 BACKGROUND OF STUDY

Fault detection in electrical power transmission systems is a critical component of power system management, ensuring stability, reliability, and efficiency. The advent of advanced technologies, such as Artificial Neural Networks (ANNs), has provided new avenues for improving fault detection mechanisms.

This research project focuses on employing ANN algorithms to enhance fault detection in the Electrical Power Transmission System in Nigeria, utilizing high-tension grid power datasets of frequency and voltage from the Transmission Company of Nigeria (TCN), which operates under the Power Holding Company of Nigeria (PHCN).

Nigeria's power transmission network, managed by TCN under the Federal Ministry of Power, is a crucial infrastructure supporting the nation's economic activities. The high-tension grid power datasets, comprising voltage and frequency measurements, provide valuable insights into the operational status of the transmission system. These datasets reflect the dynamic nature of the grid, influenced by various internal and external factors.

1.2 PROBLEM STATEMENT

The Nigerian Electric Power Transmission grid currently encounters frequent faults due to various factors such as equipment failure, environmental conditions, and human error. These faults have led to several incidences of power outages and sometimes prolonged disturbances on the entire Electric Power Grid. These occurrences have greatly hindered the industrialization and development of the nation. These faults disrupt the power supply, leading to economic losses and reduced reliability. Traditional fault detection methods have proven inadequate in addressing these issues promptly and accurately. Therefore, there is a pressing need for an advanced, efficient, and reliable fault detection system.

1.3 MOTIVATION

The current state of Electric Power instability has crippled the potential for our industrialization in so many ways in Nigeria. So many industries are unable to kickstart operations because of lack of stable power supply. Some other industries have packed up because of the same problem and the rising cost of fuel has not helped matters at all. The current state of things in the Electric Power supply sector will only degenerate until we come up with scientific approaches that will make the system better.

The gains of stable Electric Power supply cannot be quantified in any way. These gains will result in massive Industrialization and development in Nigeria as seen in so many developed countries around the world. Stable Electric Power supply has helped to push scientific and socio-economic growth in countries like Germany, France, and the United Kingdom.

1.4 AIM AND OBJECTIVES OF STUDY

This research project aims to detect faults in electrical power systems using Artificial Neural Network algorithms. The objectives are:

- Create, Train, and Test an Artificial Neural Network with Voltage and Frequency datasets from the Transmission Company of Nigeria (TCN).
- To evaluate the performance of ANN-based fault detection using voltage and frequency datasets from TCN.

- To compare the effectiveness of ANN algorithms with traditional fault detection methods.

1.4 JUSTIFICATION

Electrical Power Transmission Systems' reliability and stability are critical for ensuring uninterrupted power supply and preventing widespread outages. Faults in these systems can lead to significant economic losses, safety hazards, and operational challenges. Traditional fault detection methods, while effective, often struggle with the complexity and dynamic nature of modern power grids. This is where Artificial Neural Network (ANN) algorithms offer a promising solution.

1.5 SCOPE OF STUDY

The scope of this research project is limited to using an Artificial Neural Network algorithm to detect and report faulty frequency and voltage values which could lead to system collapse or prolonged grid disturbances. It does not include work on optimizing the values themselves. Data used for training the network was sourced from the daily broadcasts of the Transmission Company of Nigeria (TCN) for the period spanning 24th January 2023 to 24th January 2024.

1.6 SIGNIFICANCE OF STUDY

The significance of this study lies in its potential to enhance the reliability and stability of Nigeria's power transmission system. By leveraging ANN algorithms, this research aims to provide a robust and efficient fault detection mechanism, reducing downtime and maintenance costs. Moreover, the study will contribute to the existing body of knowledge by applying advanced machine learning techniques to a developing country's power system context, offering insights that could be beneficial to other similar regions.

1.7 STRUCTURE OF THIS RESEARCH PROJECT

Chapter 1

Chapter one contains a brief discussion on a brief background of the research topic, the scope, objectives, and method adopted for this research project.

Chapter 2

Chapter two contains a review of available literature on the research topic.

Chapter 3

Chapter three contains details of the method employed in the research project.

Chapter 4

Chapter four outlines the observations and results recorded in the study. This does not exclude problems encountered and precautions taken in the course of this research project.

Chapter 5

Chapter five contains a summary, conclusions, and recommendations including knowledge added through this research project.

CHAPTER TWO

LITERATURE REVIEW

2.1 OVERVIEW OF ELECTRICAL POWER TRANSMISSION

Existing research has extensively explored various fault detection methods in electrical power systems. Traditional methods, such as distance protection and differential protection, have been widely implemented but come with limitations in terms of accuracy and speed. Recent studies have demonstrated the potential of machine learning and ANN algorithms in overcoming these limitations. For instance, Alhelou et al. (2018) illustrated the effectiveness of ANNs in real-time fault detection, highlighting their adaptability and precision.

Despite these advancements, there is a notable gap in applying ANN-based fault detection in the context of Nigeria’s power transmission system. Previous research has primarily focused on developed countries, with little attention given to the unique challenges and data characteristics of Nigerian power grids. This study aims to fill this gap by leveraging ANN algorithms on Nigerian high-tension grid datasets.

2.2 BASIC CONCEPT OF ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks, inspired by the human brain's neural structure, are highly effective in pattern recognition and classification tasks. ANNs consist of interconnected neurons (nodes) that process input data and adjust their weights through training, enabling them to learn complex patterns and make accurate predictions. In the context of fault detection, ANNs can be trained on historical data to identify fault patterns based on voltage and frequency variations.

2.3 A BRIEF HISTORY OF ARTIFICIAL INTELLIGENCE

From time immemorial, the quest for improvement of the human condition has been a top priority of the human race. Man has always been out to make things easier for himself and for the world around him. This has driven the entire human race to create objects such as bows and arrows, hammers, clubs, spears, axes, clothes, machines, shelter, computers, cars, and so much more.

In his quest to be like his maker, man has been credited with creations and inventions that mimic human intelligence and display the creative attributes of his maker.

2.4 DEFINITION OF KEY TERMS

2.4.1 SMART GRIDS

According to the International Energy Agency(IEA), a Smart Grid is an Electricity Network that uses Digital and other Advanced Technologies to Monitor and Manage the Transportation of Electricity from all generation sources to meet the varying electricity demands of end users (IEA, 2024). Many Countries such as Japan, United States of America(USA), China, Australia, India, Canada, Korea, Brazil, Mexico and the UK have made huge investments towards deploying electricity networks that use digital technologies, sensors and software to better match the supply and demand of electricity in real time while minimizing costs and maintaining the stability and reliability of the grid. To this end, optimizing the Nigerian Electricity Industry by minimizing grid instability using Artificial Neural Networks is a very important subject to look into.

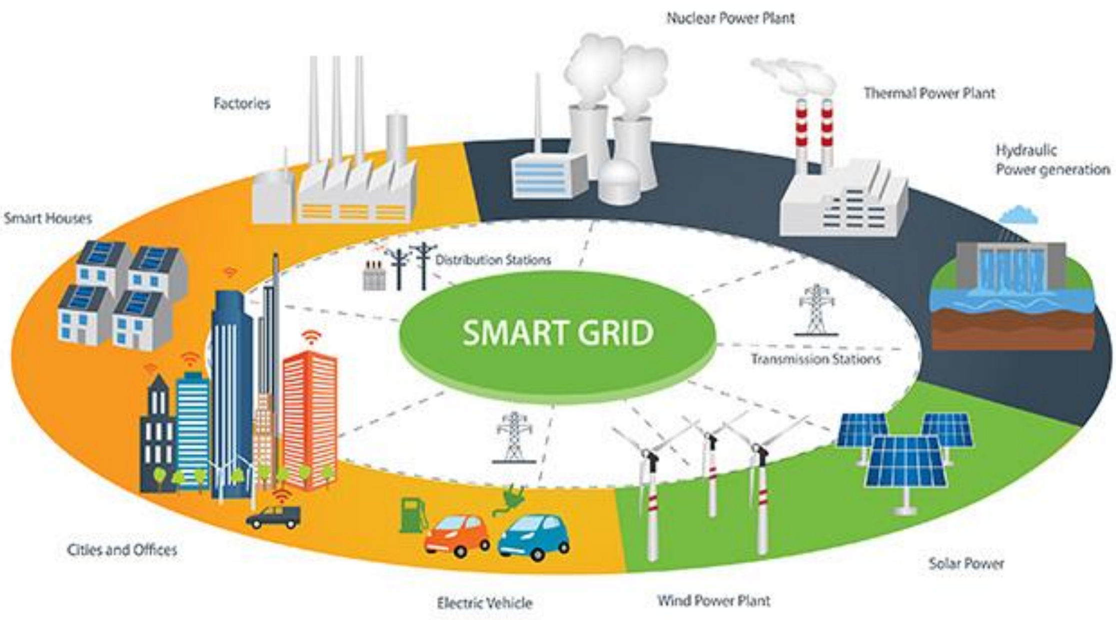


Figure 1: Image depicting a smart grid

Source: https://www.eolasmagazine.ie/smart-grid-evolution/

2.4.2 OPERATIONAL STANDARDS OF THE NIGERIAN GRID CODE

The Nigerian Grid Code, a document issued by the Nigerian Electricity Regulatory Commission (NERC, 2018) gives the following as operational standards.

- In order to maintain the security and integrity of the Transmission System, it is necessary that the System Operator operates the Transmission System and Dispatches it in such a manner as to provide adequate Frequency Control to achieve operation within applicable Frequency limits at all times.
- The nominal Frequency of the System shall be 50Hz. The National Control Centre will endeavour to control the System Frequency within a narrow operating band of +/- 0.5% from 50Hz (49.75 – 50.25 Hz), but under System Stress the Frequency on the Power System could experience variations within the limits of 50 Hz +/- 2.5% (48.75 – 51.25 Hz).

- All Equipment and Apparatus connected directly or indirectly to the National Grid must operate at 50Hz Frequency mode.
- Under extreme System fault conditions all Generating Units or Power Park Modules are permitted to disconnect (unless otherwise agreed in writing with the System Operator):

(a) at a frequency greater than or equal to 51.50 Hz, provided that for frequency excursions up to 51.75Hz of no more than 15 seconds it shall remain synchronized with the system; or

(b) at a Frequency less than or equal to 47.5 Hz.

- The System Operator shall endeavour to control the different busbar voltages to be within the Voltage Control ranges specified in the following table:

Table 1: Voltage Ranges

Voltage Level	**Minimum Voltage(kV)**	**Maximum Voltage(kV)**
330kV	280.5	346.5
132kV	112.2	145.2
66kV	62.04	69.96kV
33kV	31.02	34.98
11kV	10.45kV	11.55

Clearly, Nigeria has a policy framework in place but lacks the technology to implement said policies.

2.4.3 INTELLIGENCE

Here are a few collective definitions of Intelligence.

1. “The ability to learn, understand and make judgments or have opinions that are based on reason” Cambridge Advance Learner's Dictionary, 2006
2. “Intelligence is a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly, and learn from experience.” Common statement with 52 expert signatories (H. Masum, 2002)
3. “The ability to learn facts and skills and apply them, especially when this ability is highly developed.” Encarta World English Dictionary, 2006
4. “...ability to adapt effectively to the environment, either by making a change in oneself or by changing the environment or finding a new one ...intelligence is not a single mental process, but rather a combination of many mental processes directed toward effective adaptation to the environment.” Encyclopedia Britannica, 2006
5. “the general mental ability involved in calculating, reasoning, perceiving relationships and analogies, learning quickly, storing and retrieving information, using language fluently, classifying, generalizing, and adjusting to new situations.” Columbia Encyclopedia, sixth edition, 2006
6. “Capacity for learning, reasoning, understanding, and similar forms of mental activity; aptitude in grasping truths, relationships, facts, meanings, etc.” Random House Unabridged Dictionary, 2006
7. “The ability to learn, understand, and think about things.” Longman Dictionary of Contemporary English, 2006
8. “The ability to acquire and apply knowledge and skills.” Compact Oxford English Dictionary, 2006

Here are definitions from researchers in artificial intelligence.

1. "...the ability of a system to act appropriately in an uncertain environment, where appropriate action is that which increases the probability of success, and success is the achievement of behavioral subgoals that support the system's ultimate goal." J. S. Albus [2]

2. "Any system ...that generates adaptive behviour to meet goals in a range of environments can be said to be intelligent." D. Fogel (Fogel., 1995)

3. "Achieving complex goals in complex environments" B. Goertzel (Goertzel., 2006)

4. "Intelligent systems are expected to work, and work well, in many different environments. Their property of intelligence allows them to maximize the probability of success even if full knowledge of the situation is not available. Functioning of intelligent systems cannot be considered separately from the environment and the concrete situation including the goal." R. R. Gudwin (Gudwin, 2000)

5. "[Performance intelligence is] the successful (i.e., goal-achieving) performance of the system in a complicated environment." J. A. Horst (Horst, 2002)

6. "Intelligence is the ability to use optimally limited resources – including time – to achieve goals." R. Kurzweil (Kurzweil, 2000)

7. "Intelligence is the power to rapidly find an adequate solution in what appears a priori (to observers) to be an immense search space." D. Lenat and E. Feigenbaum (Feigenbaum., 1991)

8. "Intelligence measures an agent's ability to achieve goals in a wide range of environments." S. Legg and M. Hutter (Hutter, 2006)

9. "...doing well at a broad range of tasks is an empirical definition of `intelligence' " H. Masum (H. Masum, 2002)

10. “Intelligence is the computational part of the ability to achieve goals in the world. Varying kinds and degrees of intelligence occur in people, many animals and some machines.” J. McCarthy (McCarthy, 2004)

11. “...the ability to solve hard problems.” M. Minsky (Minsky, 1985)

12. “Intelligence is the ability to process information properly in a complex environment. The criteria of properness are not predefined and hence not available beforehand. They are acquired as a result of the information processing.” H. Nakashima (Nakashima, 1999)

13. “...in any real situation behavior appropriate to the ends of the system and adaptive to the demands of the environment can occur, within some limits of speed and complexity.” A. Newell and H. A. Simon (Simon, 1976)

14. “[An intelligent agent does what] is appropriate for its circumstances and its goal, it is flexible to changing environments and changing goals, it learns from experience, and it makes appropriate choices given perceptual limitations and finite computation.” D. Poole (D. Poole, 1998)

15. “Intelligence means getting better over time.” Schank (Schank., 1991)

16. “Intelligence is the ability for an information processing system to adapt to its environment with insufficient knowledge and resources.” P. Wang (Wang., 1995)

17. “...the mental ability to sustain successful life.” K. Warwick quoted in (Asohan., 2003)

18. “...the essential, domain-independent skills necessary for acquiring a wide range of domain-specific knowledge – the ability to learn anything. Achieving this with `artificial general intelligence' (AGI) requires a highly adaptive, general-purpose system that can autonomously acquire an extremely wide range of specific knowledge

and skills and can improve its own cognitive ability through self-directed learning." P. Voss (Voss., 2005)

2.4.4 ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI) is the capacity of a computer or robot under computer control to carry out operations typically performed by intelligent entities. The phrase is commonly used to describe the endeavor of creating artificial intelligence systems that include human-like cognitive functions, like reasoning, meaning-finding, generalization, and experience-based learning. It has been shown that computers are capable of performing extremely complicated jobs, including finding proofs for mathematical theorems or playing chess, with remarkable proficiency ever since the digital computer was developed in the 1940s (Copeland, 2024).

Nevertheless, despite ongoing improvements in computer memory and processing power, no software can yet fully mimic human adaptability over a larger range of areas or in jobs requiring a great deal of common knowledge. However, in certain limited applications, such as medical diagnosis, computer search engines, voice or handwriting recognition, and chatbots, artificial intelligence has evolved to the point where some programs can perform at the same levels as human experts and professionals (Copeland, 2024).

2.4.5 EXAMPLES OF ARTIFICIAL INTELLIGENCE

2.4.5.1 SPEECH RECOGNITION

Speech recognition, also known as automatic speech recognition (ASR), computer speech recognition, or speech-to-text, is a capability which enables a program to process human speech into a written format. While it's commonly confused with voice recognition, speech recognition focuses on the translation of speech from a verbal format to a text one whereas voice recognition just seeks to identify an individual user's voice (IBM, 2024).

2.4.5.2 ROBOTICS

Robotics is a branch of AI, which is composed of Electrical Engineering, Mechanical Engineering, and Computer Science for designing, construction, and application of robots (tutorialspoint.org, 2024).

Robots are aimed at manipulating the objects by perceiving, picking, moving, modifying the physical properties of object, destroying it, or to have an effect thereby freeing manpower from doing repetitive functions without getting bored, distracted, or exhausted.

2.4.5.3 ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANNs) have the potential to be trained to overcome the restrictions of the traditional methods to solve complex problems. This technique learns from given examples by constructing an input–output mapping in order to perform estimations. Neural networks consist of an inter-connection of a number of neurons which mimic the behaviour of the human brain. (Kaytez, Taplamacioglu, Cam, & Hardalac, 2014).

The idea of ANNs is based on the belief that the working of the human brain by making the right connections, can be imitated using silicon and wires as living neurons and dendrites.

The human brain is composed of over 85 billion nerve cells called neurons. They are connected to other thousand cells by Axons. Stimuli from external environment or inputs from sensory organs are accepted by dendrites. These inputs create electric impulses, which quickly travel through the neural network. A neuron can then send the message to other neuron to handle the issue or does not send it forward. (tutorialspoint.org, 2024)

2.4.5.4 MACHINE LEARNING

Machine learning is a branch of artificial intelligence (AI) and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy. (IBM, 2024)

2.4.5.5 NATURAL LANGUAGE PROCESSING

Natural Language Processing (NLP) refers to AI method of communicating with an intelligent system using a natural language such as English.

Processing of Natural Language is required when you want an intelligent system like robot to perform as per your instructions, when you want to hear decision from a dialogue based clinical expert system, etc. (tutorialspoint.org, 2024)

The field of NLP involves making computers to perform useful tasks with the natural human languages.

2.4.5.6 COMPUTER VISION

This is a technology of AI with which the robots can see. Computer vision plays vital role in the domains of safety, security, health, access, and entertainment.

Computer vision automatically extracts, analyzes, and comprehends useful information from a single image or an array of images. This process involves the development of algorithms to accomplish automatic visual comprehension. (tutorialspoint.org, 2024)

2.4.5.7 EXPERT SYSTEMS

Expert systems are computer applications developed to solve complex problems in a particular domain, at the level of extraordinary human intelligence and expertise. They remain a vital aspect of Artificial Intelligence which has found application in medicine, engineering, and other fields of human endeavour. (tutorialspoint.org, 2024)

2.5 APPLICATIONS OF ARTIFICIAL INTELLIGENCE

2.5.1 ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN WASTE MANAGEMENT

Rapid urbanization, population growth, and economic development have increased waste generated worldwide in recent years. According to the latest statistics, 2.01 billion tonnes of municipal solid waste was generated globally in 2016. This figure is expected to increase to 3.4 billion tonnes by 2050 (Kaza S, Yao L, Bhada-Tata P, & F., 2018). Unfortunately, 33% of solid waste is managed correctly and disposed of in illegal dumpsites or unmonitored landfills (Kaza S, Yao L, Bhada-Tata P, & F., 2018). Improper waste disposal poses many environmental and health risks, such as groundwater contamination, land degradation, increased cancer incidence, child mortality, and congenital disabilities (Triassi M, et al., 2015). In the past, waste management practices were more rudimentary, with a small group of individuals collecting garbage from the streets and depositing it in designated areas (Brancoli P, Bolton K, & M., 2020). Once the trucks were full, the waste was left in these designated areas. However, with the advent of artificial intelligence, the waste management industry is experiencing significant transformation toward achieving sustainability and profitability (Fang., 2023).

Artificial intelligence is a rapidly advancing technology that is gaining popularity in various industries, particularly waste management (Abdallah M, et al., 2020). The incorporation of artificial intelligence and robotics in the design and operation of urban waste treatment plants can revolutionize how solid waste is managed, leading to increased operational efficiency and more sustainable waste management practices (Fang., 2023). Several developed countries, including Austria, Germany, New Zealand, the USA, the UK, Japan, Singapore, Switzerland, South Korea, and Canada, have already begun to adopt artificial intelligence technologies to maximize resource utilization, efficiency, and recycling opportunities throughout the solid waste management cycle (Soni U, Roy A, Verma A, & V., 2019). Artificial intelligence technologies, particularly for sorting and treating solid waste, are increasingly critical in waste management (Andeobu L, Wibowo S, & S., 2022).

Therefore, artificial intelligence is critical in developing sustainable waste management models, particularly for transitioning to a “zero waste circular economy” while considering social, economic, and environmental factors (Osman AI, et al., 2022). Waste management should be considered when examining the problems facing different geographic areas and economic sectors, including smart cities.

For instance, researchers have proposed various models for sustainable waste management, such as a model for megacities that considers waste treatment, recycling, and reuse options (P., 2009). To choose the best location for solid waste management system components, another model was developed by researchers that takes into account uncertain waste generation rates, facility running costs, transportation costs, and revenue (Chadegani AA, et al., 2013).

Based on the England panel data, some researchers (Liu Y, Kong F, & EDR., 2017) investigated data on landfill, waste management, and environmental safety in England, including the reasons for illegal dumping (Goutam Mukherjee A, et al., 2021). In addition, some scholars emphasized the need for a new school of management thought to transition to a "zero waste circular economy." (Zhang A, et al., 2019)

The Figure below shows the key concepts of artificial intelligence in waste management.

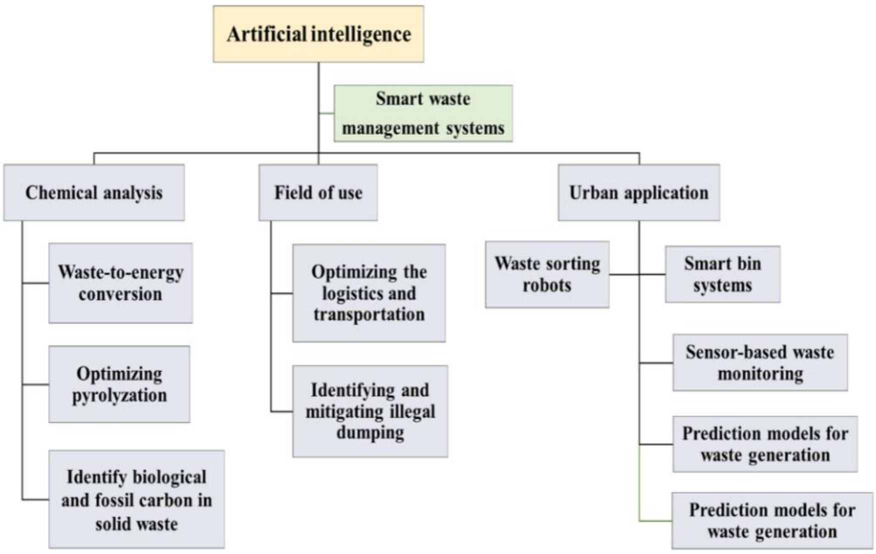


Figure 2: Application of artificial intelligence in waste management.
Source (Fang., 2023)

The figure above illustrates five key aspects: waste type and generation, the use of artificial intelligence in waste management, artificial intelligence-based optimization of waste transportation, the role of artificial intelligence in detecting and reducing illegal dumping and waste treatment practices, and the use of artificial intelligence to analyze the chemical composition of waste.

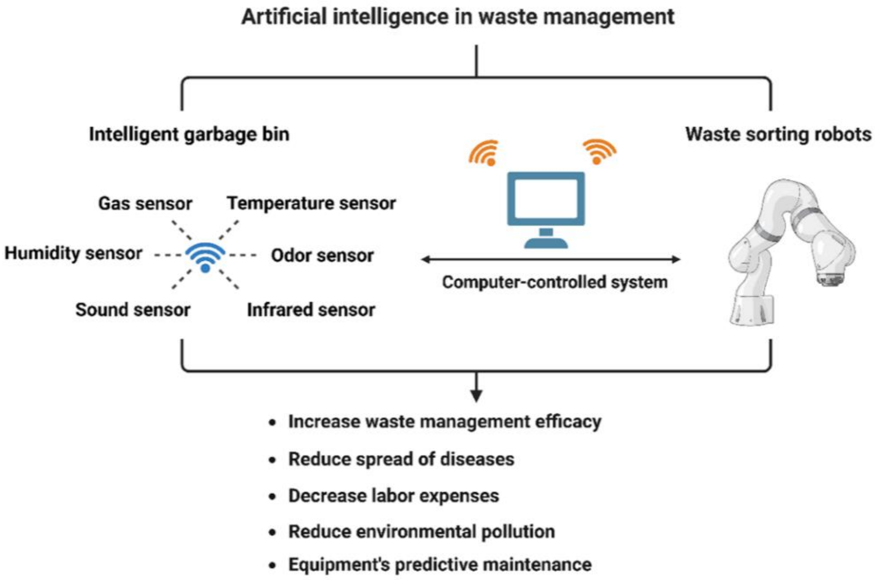


Figure 3: Uses of artificial intelligence in the garbage bin and waste robotic sorting. Source (Fang., 2023)

The figure above illustrates a more detailed view of the uses of artificial intelligence in waste management. These include real-time garbage bin monitoring to optimize waste collection routes and prevent bin overflows. Additionally, intelligent garbage sorting can improve recycling efficiency and reduce contamination. In contrast, robotic waste sorting can utilize robotic arms to sort waste in recycling facilities, increasing the speed and accuracy of sorting while reducing the need for manual labour (Fang., 2023).

Artificial intelligence can also be used for predictive maintenance to anticipate when waste-sorting equipment will require maintenance, reducing downtime and extending equipment lifespans. Lastly, waste management optimization using artificial intelligence can consider factors such as traffic, weather, and population density to enhance the efficiency of waste collection and processing odor, infrared, gas, and sound sensors. Increase waste management efficacy (Fang., 2023).

2.5.2 ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN PREDICTIVE ANALYTICS

The growth of sensing technology has led to an exponential increase in the amount of data gathered from production operations. Data can extract useful information and knowledge from production systems, machinery, and manufacturing processes when it is processed and examined. Equipment maintenance plays a critical role in industries, impacting both the equipment's operational duration and efficiency. Therefore, in order to prevent manufacturing processes from being shut down, equipment problems must be located and fixed. In Predictive Maintenance (PdM) applications, machine learning (ML) techniques have emerged as a promising tool to prevent equipment breakdowns in the production lines on the factory floor. (Carvalho, et al., 2019)

Currently, the Technology industry is going through what experts have called “The Fourth Industrial Revolution”, also called Industry 4.0. This fact is strongly associated with the integration between physical and digital systems of production environments. The integration of these environments allows the collection of a large amount of data that is collected by different equipment, located in different sectors of the factories (Borgi, 2017). In addition, new technologies from Industry 4.0 integrate people, machines and products, enabling faster and more targeted exchange of information (Carvalho, et al., 2019).

The big amount of data, collected by industrial systems, contains information about processes, events and alarms that occur along an industrial production line. Moreover, when processed and analyzed, these data can bring out valuable information and knowledge from manufacturing process and system dynamics. By applying analytic approaches based on data, it is possible to find interpretive results for strategic decision-making, providing advantages such as, maintenance cost reduction, machine fault reduction, repair stop reduction, spare parts inventory reduction, spare part life increasing, increased production, improvement in operator safety, repair verification, overall profit, among others (Peres, 2018).

The mentioned advantages have strong relationship with maintenance procedures. In industries, equipment maintenance is an important key, and affects the operation time of equipment and its efficiency. Therefore, equipment faults need to be identified and solved, avoiding shutdown in the production processes (Carvalho, et al., 2019). For example, Vafaei (Vafaei, 2019) propose a fuzzy alarm system to predict early equipment degradation in a car production line, with the aim of reducing costs with sudden shutdowns. Wei (Wei, 2019) propose a condition-based maintenance strategy to determine the optimal action (e.g., no action and corrective replacement) based on the system state in order to minimize the average cost rate. On the other hand, (Dong, 2019) developed a prognostic and health management framework to detect sensor degradation in manufacturing systems in order to optimize the maintenance scheduling, with the aim of reducing maintenance cost, avoiding unnecessary down-times and supporting decision-making.

Different nomenclature and groups of maintenance management strategies can be found in literature. Some Proposed a number of categories (Carvalho, et al., 2019). They classify the maintenance procedures as follows:

2.5.2.1 RUN-TO-FAILURE (R2F) OR CORRECTIVE MAINTENANCE

This happens only when an equipment stops working. It is the simplest maintenance strategy, since it is necessary both the stop on the production and the repair of the parts to be replaced, adding a direct cost to the process.

2.5.2.2 PREVENTIVE MAINTENANCE (PVM)

Time-based maintenance or Scheduled maintenance is a maintenance technique performed periodically with a planned schedule in time or process iterations to anticipate process/equipment failures. It is generally an effective approach to avoid failures. However, unnecessary corrective actions are taken, leading to an increase in operating costs.

2.5.2.3 PREDICTIVE MAINTENANCE (PDM)

This uses predictive tools to determine when maintenance actions are necessary. It is based on continuous monitoring of a machine or a process integrity, allowing maintenance to be performed only when it is needed. Moreover, it allows the early detection of failures thanks to predictive tools based on historical data (e.g. machine learning techniques), integrity factors (e.g. visual aspects, wear, coloration different from original, among others), statistical inference methods and engineering approaches.

Machine Learning (ML), within artificial intelligence, has emerged as a powerful tool for developing intelligent predictive algorithms in many applications. ML approaches have the ability to handle high dimensional and multivariate data, and to extract hidden relationships within data in complex and dynamic environments (such as, industrial environments) (Carvalho, et al., 2019). Therefore, ML provides powerful predictive approaches for PdM applications. However, the performance of these applications depends on the appropriate choice of the ML technique.

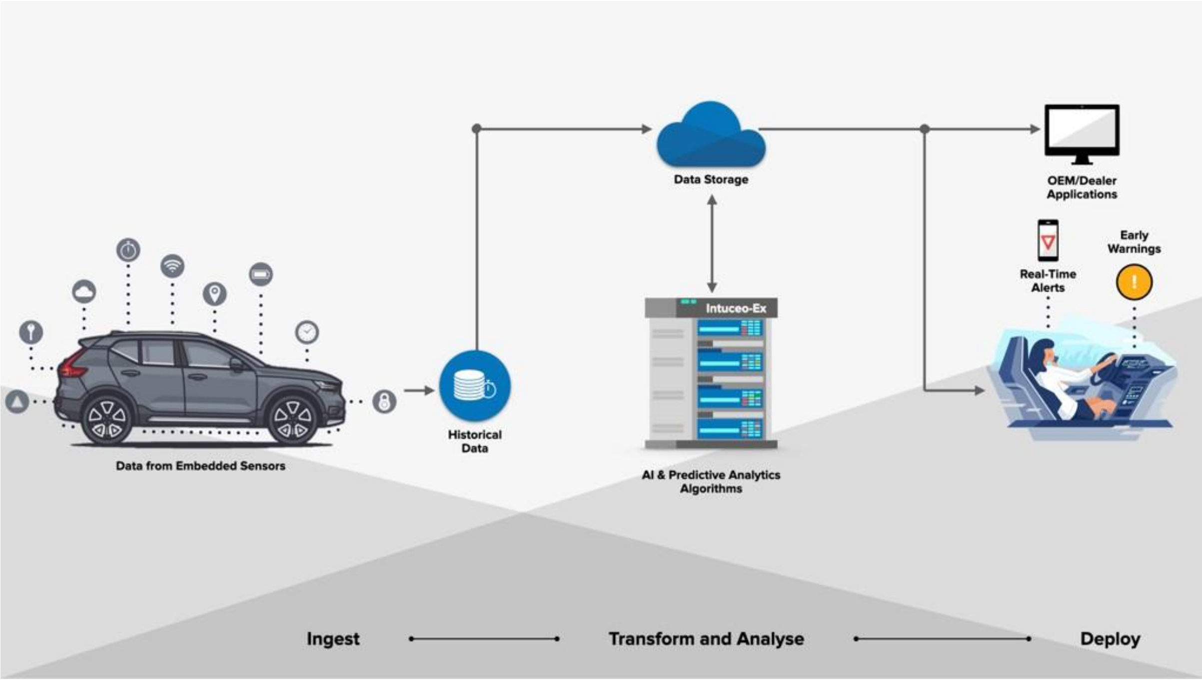


Figure 4: Image Depicting the use of AI and ML in Predictive Maintenance services

Source (https://www.analyticsvidhya.com/blog/2022/07/application-of-ai-in-predictive-maintenance-of-vehicles/)

2.5.3 ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN FINANCE

Machine learning is a powerful branch of Artificial Intelligence that has widespread applications in banking and finance. It enables financial institutions to detect fraudulent transactions, and assists managers in credit scoring, ranking and granting decisions. Financial Robo-advisors and chatbots provide banking assistance to clients, asset allocation systems provide risk-return assessments to investors whilst automated insurance services are available to policyholders; the financial applications of Machine learning are interminable (Nazareth & Ramana Reddy, 2023). With its ability to process massive quantities of data and simultaneously accommodate non-linearities in data, Machine learning has emerged at the forefront of statistics. Recent decades have witnessed a great deal of research using computational intelligence in finance (Nazareth & Ramana Reddy, 2023). Also, Recent studies have compiled and reviewed the recent advancements of Machine learning in six financial areas: stock markets, portfolio management, forex markets, bankruptcy and insolvency, financial crisis, and cryptocurrency. It examines the models: k-Nearest Neighbours, Bayesian classifiers, decision trees, Random Forest, Support Vector Machine, Deep learning models such as Artificial Neural Network/Deep Neural Network, Feed Forward Neural Network, Back Propagation Neural Network, Multilayer Perceptron, Convolutional Neural Network, Recurrent Neural Network, Long Short-Term Memory, Gated Recurrent Units, Reinforcement learning models, hybrid and ensemble models; and identifies its appropriate applicability in specific fields to solve various financial problems (Nazareth & Ramana Reddy, 2023).

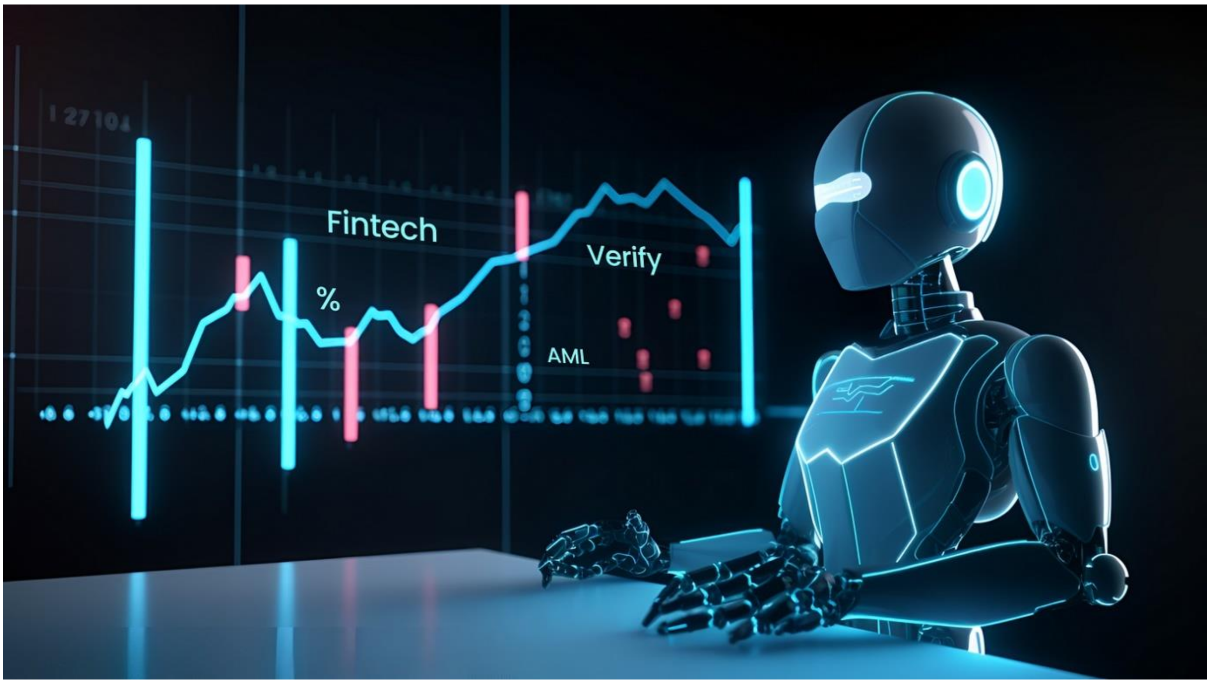


Figure 5: Image Depicting the use of AI and ML in Financial services

Source(https://zoop--one.medium.com/revolutionizing-fintech-top-10-applications-of-artificial-intelligence-356709907723)

2.5.4 ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN AGRICULTURE

Sustainability in the agricultural sector is the key to ensure food security and hunger eradication for the ever-growing population. It is estimated that global food production must be increased by 60–110% to feed 9–10 billion of the population by 2050 (Sharma, Kamble, Gunasekaran, Kumar, & Kumar, 2020). It is therefore required to have a strategic shift from the current paradigm of enhanced agricultural productivity to agricultural sustainability. Sustainable agriculture practices not only focus on enriching agricultural productivity but also help to reduce harmful environmental impacts. The sustainable Agriculture Supply Chains (ASCs) are knowledge-intensive and are based on information, skills, technologies, and attitudes of the supply chain partners (Sharma, Kamble, Gunasekaran, Kumar, & Kumar, 2020). Knowledge transfer encourages farmers to enhance their decision to adopt sustainable agriculture practices (SAP) (Adnan, 2018). Some writers claim that the ASCs are facing tremendous pressure to increase the farming efficiency, which is driven by the depleting rate of water and fossil fuels, shrinking availability of arable land and the increasing demand by the consumers for more transparent and sustainable food chains (Duman, 2017). The need for the ASCs to respond to the increasing demand and supply gaps, as well as market price fluctuations, is also identified as critical drivers of farming efficiency. Further, recent studies covering the sustainable aspects of inventory and transportation management concerning the perishable items may help us to understand the complexities involved in achieving sustainable ASCs. The digital technologies that include the internet of things (IoT), mobile technologies and devices, data analytics, artificial intelligence

(AI), digitally delivered services, and other applications are influencing the ASCs (Sharma, Kamble, Gunasekaran, Kumar, & Kumar, 2020). Numerous examples demonstrate the use of digital technologies at different stages of ASC such as automation of farm machinery resulting in reduced labour input, use of sensors and remote satellite data for improved monitoring of crops, land, and water, IoT and RFID for agriculture product traceability.

With advancements in digital technology, a large amount of data is getting generated in the supply chains, which is useless unless it is organized, understood, and meaningful insights are gained using appropriate data analysis tools. AI or cognitive-based technologies is the most transformative and impactful advanced analytics tool that can be used by organizations for supply chain decision-making (Sharma, Kamble, Gunasekaran, Kumar, & Kumar, 2020). AI helps computers interact, reason, and learn like human beings to enable them to perform a wide variety of cognitive tasks, usually requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages and demonstrating an ability to move and manipulate objects accordingly. Intelligent systems use a combination of big data analytics, cloud computing, machine-to-machine communication, and the IoT to operate and learn. Machine and deep learning algorithms, the subsets of AI, are widely used in combination with location intelligence technologies in ASC to identify hidden patterns in the data (Elavarasan, 2018). Studies published in Forbes suggest ASC practitioners consider AI and advanced analytics as strategic investments because of the accelerating digital transformation in ASC and need to develop a competitive advantage (Sharma, Kamble, Gunasekaran, Kumar, & Kumar, 2020). Some scholars have described how information technology (IT) is impacting the expectations of farmers as well as customers and accordingly, their demand is changing (Sharma, Kamble, Gunasekaran, Kumar, & Kumar, 2020).

Figure 6: Practical application of AI and ML in Agriculture.

Source (https://www.bearingtips.com/precision-agriculture-the-hype-around-drone-technology/)

2.5.5 ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN MEDICINE

Big data and technological innovation have revolutionized medicine and healthcare over the last decade (Esteva A, et al., 2019). Today, advanced technological solutions are able to generate health and medical data at the individual level in real time and in a real-world environment. They are at the core of such digital disruption that holds promise for improving the practice of medicine towards a more targeted and personalized paradigm, enabled by data-driven decisions based on real-world evidence, patient-participatory drug development, and healthcare democratization. In recent years, pharmaceutical Research and Development (R&D) has transformed to a highly dynamic process enabled by patient-centered iterative forward and reverse translation. Traversing the path from idea to medicine has become increasingly multi-disciplinary and inter-connected, as exemplified by the Drug Discovery, Development, and Deployment Map, illustrating a network view of the process and associated cross-sector ecosystem, challenging the typical chevron (linear, sequential, left to right) view of pharmaceutical R&D pipeline (J, et al., 2018). A Bayesian learning mindset that exploits the totality of evidence is particularly important in timely delivery of innovative healthcare solutions to address unmet medical needs with the right sense of urgency (K & J., 2018) (K., O., JQ., & LJ., 2020) (R., P., J., R., & MP., 2020).

Whereas advances in biology, biomedical engineering, and computational sciences have resulted in an explosive increase in our ability to generate and store multi-dimensional data from diverse sources (e.g., laboratory, clinical trial, real-world, literature), consistent real-time integration of these data for principled and timely decision making in pharmaceutical R&D and healthcare remains aspirational (F. & A., 2019). Recognizing this critical importance of optimal knowledge management, the pharmaceutical industry has started building digital capabilities and embracing innovations in Data Science into their Research and Development (R&D) organizations (Hird N, Ghosh S, & H., 2016). Machine learning (ML), deep learning (DL) and more generally artificial intelligence (AI) techniques are central components of this innovation. While AI refers to the output of a computer generated by mimicking a human behavior and it does not say how the problem has been solved, ML is a subset of AI consisting of a set of algorithms that parse data, learn from them, and then apply learnings to make intelligent decisions. A simple and widely used classification of ML algorithms is into supervised, unsupervised, DL and then reinforcement learning. Supervised learning is task driven and it is used for classification and prediction tasks on new data by starting on datasets with known labels or outcomes. Differently, unsupervised learning methods are data driven and focus on finding structures and patterns inside the data itself. Examples include finding groups and clusters (clustering), understanding relationships between items (association rule mining), and finding a more compact representation of the data (dimension reduction). Reinforcement learning uses algorithms interactively learning to react to an environment from mistakes by focusing on decision and policy making. Lastly, inspired by the biological neural network (NN) of the human brain, DL uses NNs with many layers (more than one hidden layer to be considered deep) to solve the hardest (for computers) problems. Such process of learning is far more capable than that of standard ML models. Indeed, while both ML and DL fall under the broad category of AI, DL is what powers the most human-like artificial intelligence (Terranova, Venkatakrishnan, & Benincosa, 2021).

Owing to their ability to learn hidden and predictive patterns in large amounts of heterogenous and high-dimensional datasets, AI techniques have been increasingly adopted across the drug discovery and development value chain (Vamathevan J, et al., 2019). Initially, AI methods were mostly used in drug discovery to analyze large sets of chemical structure data, gene expression and genetic data, and high throughput in vitro data (Chan HCS, Shan H, Dahoun T, Vogel H, & S., 2019). Optimization of drug candidates towards better drug properties has been an area of sustained focus of AI/ML frameworks in drug discovery, enabling efficient iterative approaches to multi-dimensional optimization based on virtual screening and prediction of physicochemical properties and biological activity and toxicity (Chan HCS, Shan H, Dahoun T, Vogel H, & S., 2019). More recently, a wide range of ML applications have emerged as promising approaches to generate new knowledge in translational and clinical drug development (Shah P, et al., 2019). Together with the automation of process pipelines and operational design, the integration and analysis of large, multi-dimensional, and heterogenous data sets, such as -omics data, information from wearable devices, images, and electronic health records, offers an unprecedented opportunity for AI/ML applications in drug development. The associated contexts of use range broadly from advancing understanding of the disease and its underlying physiological and biological underpinnings, elucidation of drug mechanism of action (MoA) and identification of promising combinations, characterization of sources of population variability in patients' response, and enhancement of trial design and operational efficiency, diagnosis, individualized treatment, and precision dosing solutions (Finelli LA & V., 2020) (Inan OT, et al., 2020) (Bica I, Alaa AM, Lambert C, & M., 2020).

The integration and use of AI/ML methods across the translational through clinical drug development continuum have already demonstrated a clear impact on our ability to successfully maximize the value of data. Furthermore, these methods have enhanced knowledge management both with respect to the studied drug and the disease/patient population, thereby enabling optimization of R&D across the three key inter-dependent strategic pillars that constitute the practice of Translational Medicine: target, patient, and dose (Dolgos H, et al., 2016). These pillars represent the fundamental pivots for hypothesis generation and ultimately for data-driven knowledge generation from preclinical, clinical, and regulatory evaluations designed to build a body of scientific evidence to achieve clinical proof of concept of innovative investigational therapies. Robust and efficient data-driven optimization alongside these three pillars is crucial to maximize probability of success in clinical development and ultimately to successfully impact product registration, labeling, and guidance for therapeutic use at the right dosage and in the context of applicable personalized medicine strategies in concert with companion diagnostics where relevant, to maximize benefit/risk across populations and clinical contexts of use. A quantitative mindset that collaboratively synergizes the disciplines of biomarker sciences, pharmacometrics, systems pharmacology, and bioinformatics is vitally important to the successful practice of Translational Medicine (Venkatakrishnan K, et al., 2020). Accordingly, advanced analytics represents a key

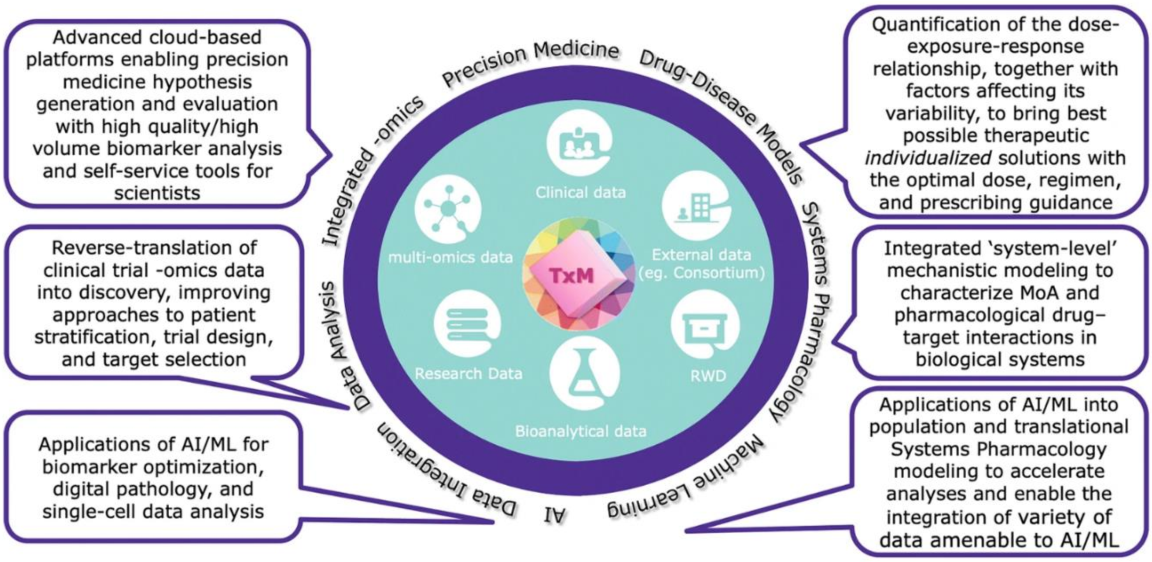


Figure 7: Application of Artificial Intelligence and Machine Learning in Medicine. Source (Venkatakrishnan K, et al., 2020)

The application of AI and ML in drug discovery and development is growing. The pharmaceutical industry has already embarked on a journey of digital transformation by bridging data silos and implementing technological solutions for a more efficient use of data generated across R&D pipelines. Given its data- and question-driven strategic foundation, Translational Medicine must be ready to embrace and integrate such tools to augment conventional approaches and nurture new cross-functional collaborations that can maximize the value of data. As such, in cross-functional pharmaceutical R&D team settings, joint efforts of Clinical Pharmacology, Bioinformatics, and Biomarker Technology experts is vital to realize the promise of AI/ML-enabled Translational and Precision Medicine. The successful adoption of these methods requires (i) a clear definition of the context of use and (ii) data needs including quantity and quality requirements; and (iii) a fit-for-purpose approach thus ensuring that the application of ML is guided by sound rationale and aimed at addressing questions justifying the additional benefit of adopting these new approaches over conventional ones. Furthermore, interoperability considerations and validation, generalizability, and interpretability of models are crucial for scalability and confidence in results for the intended applications (Terranova, Venkatakrishnan, & Benincosa, 2021). For the latter, special attention should be made to ensure that models are interpretable and reproducible, enabling biological insights to be extracted directly or by integrating interpretable output into more mechanism-based analytical methods that are more conventionally used. In fact, ML and especially DL approaches have often been criticized for their dependency on large amounts of training data and the lack of intuition associated with the generated features. However, methods are being developed to improve the interpretability and visualization of results, thus overcoming the black-box nature of some algorithms. Among these, the adoption of SHAP has greatly increased the understanding of feature importance from its local to global contribution to the ML model's prediction. Another key aspect to consider is the generalization of the ML model to new, unseen data, still representative of the wider considered population. In this respect, as for other data-driven predictive models, online retraining of an ML model should be based on the most recent data sources. Furthermore, it is important to avoid sampling bias by ensuring a diverse training dataset leading to results that can be generalized to the entire studied population. It is also important to be aware of co-segregation among covariates, including “hidden” non-observed causal factors, that can impact the interpretation of identified predictors and their relative importance. On the other hand, ML methods have been shown to offer competitive advantages over conventional methods, especially when the integration and analysis of large, multi-dimensional, and heterogeneous data sets is in scope. A highly interdependent and iterative interplay across the disciplines of Quantitative Systems Pharmacology and Pharmacometrics is envisioned. Big data and advanced technologies, including but not limited to AI and ML, hold substantial promise to enable effective forward and reverse translational discovery of sources of variation in benefit-risk profiles to ultimately bring the right therapeutic solution to all patients and make precision medicine a reality (Terranova, Venkatakrishnan, & Benincosa, 2021).

2.5.6 ARTIFICIAL NEURAL NETWORKS IN POWER SYSTEMS

The fields of machine learning (ML) and artificial intelligence (AI) have advanced power systems significantly. Here are a few noteworthy uses:

2.5.6.1 Load Forecasting

Artificial intelligence (AI) models can reliably forecast power consumption, assisting utilities in resource allocation and grid management. (Malik, 2018)

2.5.6.2 Fault Detection and Diagnosis

Machine learning algorithms examine system data to find errors, pinpoint their root causes, and suggest fixes. (Malik, 2018)

2.5.6.3 Energy Management

AI minimizes expenses, controls storage systems, and modifies loads to maximize energy use. (Malik, 2018)

2.5.6.4 Smart Grids

ML predicts outages and optimizes grid operations to help develop adaptive, self-healing grids. (Malik, 2018)

2.5.6.5 Renewable Energy Integration

Artificial Intelligence helps to integrate renewable energy sources like solar and wind into the system by predicting their output and controlling variations. (Malik, 2018)

2.5.6.6 Predictive Maintenance

ML models foretell equipment malfunctions, allowing for prompt maintenance and minimizing downtime. (Malik, 2018)

2.5.6.7 Voltage Control

AI systems control voltage to provide a steady supply of electricity. (Malik, 2018)

2.5.6.8 Security and Anomaly Detection

ML identifies anomalous power system behavior and cyberthreats. (Malik, 2018)

2.5.6.9 Optimal Dispatch

AI maximizes the production and distribution of power to reduce expenses and pollution. (Malik, 2018)

2.5.6.10 Insulation Deterioration Estimation

Transformer insulation life is estimated by Bayesian networks using historical data. (Malik, 2018)

These applications improve power systems' sustainability, efficiency, and dependability, paving the way for a more intelligent and resilient energy future.

2.6 THE NECESSITY OF THIS RESEARCH WORK

Having considered various existing literature in Artificial Intelligence and Machine learning, it's important to also state why this research project is necessary.

Looking at the Nigerian power sector, there is a lot of data generated from our national grid which if used well, will save the nation a lot of blackouts and grid collapses.

This research project focuses on using Artificial Intelligence methodologies to optimize/improve the power sector. Particularly, we shall be making use of Artificial Neural Networks to implement this.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 INTRODUCTION

In this chapter, the methodology of this research project shall be examined. Further information is given about the research strategy, the research method, the research approach, the method of data collection, the selection of the sample, the research process, the type of data analysis, the precautions/ethical considerations, and the research limitations of the project.

3.2 ARTIFICIAL NEURAL NETWORK TOPOLOGIES

There are different types of Artificial Neural Network topologies. They are

3.2.1 FEEDFORWARD ARTIFICIAL NEURAL NETWORK

Feedforward artificial neural networks are different from recurrent neural networks in that their node connections are arranged in a way that does not result in cycles between the nodes. The way information flows through the network—from the input layer to the output layer via hidden layers and forward without looping back—gives rise to the term "feedforward." (educative.io, 2024).

Below is a diagram of a Feedforward Artificial Neural Network

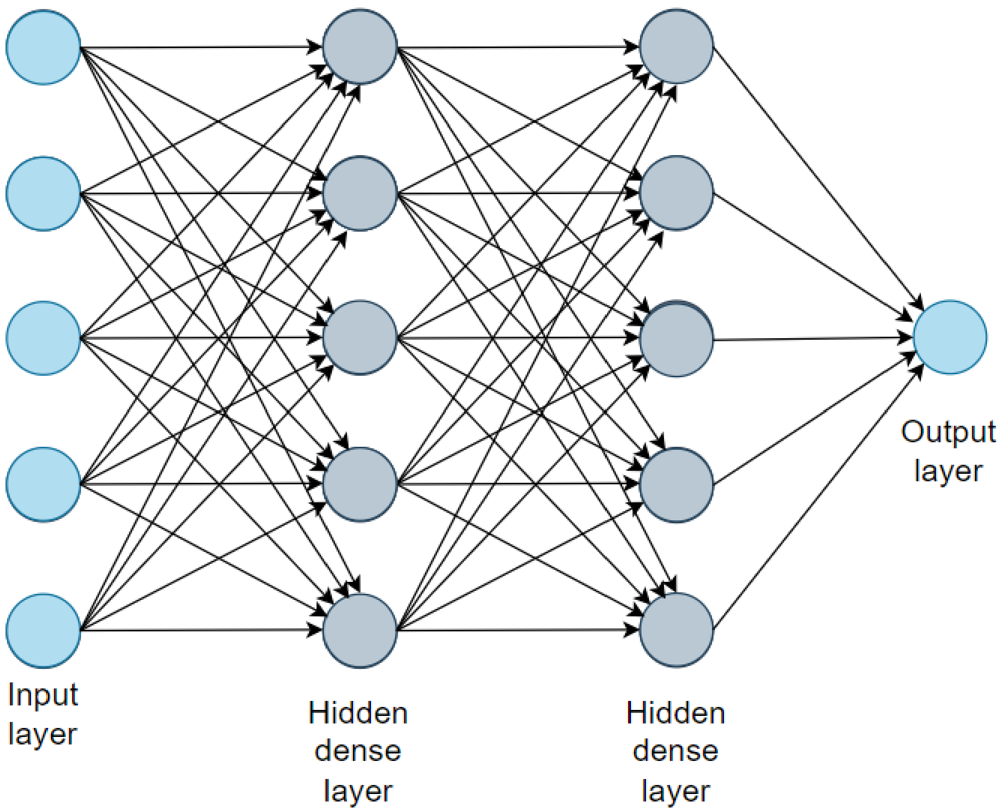


Figure 8: Diagram of a Feedforward Artificial Neural Network.

Source (educative.io, 2024)

3.2.1.1 ANATOMY OF A FEEDFORWARD ARTIFICIAL NEURAL NETWORK

A feedforward artificial neural network is made up of multiple layers of nodes or 'neurons.' These layers include:

3.2.1.1.1 INPUT LAYER

This is the starting point of the feedforward artificial Neural. Initial data is usually fed into the neural network through this layer. Each node in this layer corresponds to a feature in the dataset. The number of nodes equals the number of features.

3.2.1.1.2 HIDDEN LAYER(S)

Hidden layers, situated between the input and output layers, constitute an essential part of a feedforward artificial neural network. This is the intermediate layer between the input and output layers, and it is usually the place where all computations are done. The network can include one or multiple hidden layers, and each neuron within these layers employs a nonlinear activation function.

3.2.1.1.3 OUTPUT LAYER

The output layer is the network's endpoint. The output layer transforms the values from the last hidden layer into a format suitable for the task at hand. Simply put, it is the layer where the results are produced for a given input.

3.2.2 FEEDBACK OR RECURRENT ARTIFICIAL NEURAL NETWORK

One of the two main categories of artificial neural networks is the recurrent neural network (RNN), which is distinguished by the direction of information flow between its layers. It is a bi-directional artificial neural network, which means that it permits the output from some nodes to influence subsequent input to the same nodes, in contrast to the uni-directional feedforward neural network. (Wikipedia.org, 2024)

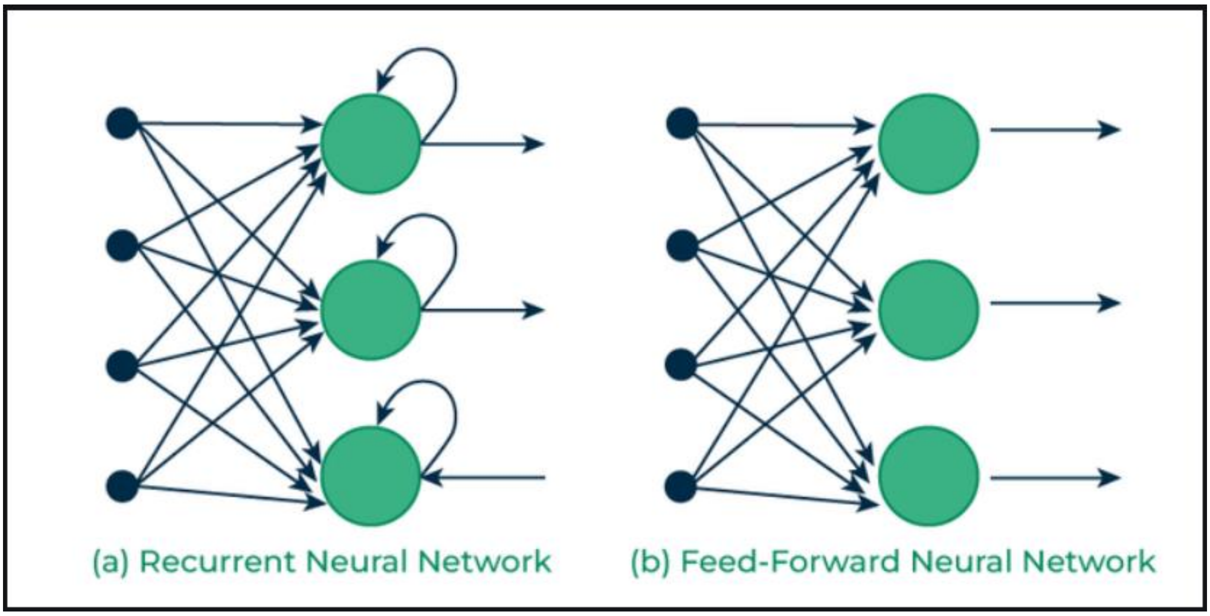


Figure 9: Recurrent vs Feedforward Neural Networks.

Source (geeksforgeeks.org, 2024)

There are four types of RNNs based on the number of inputs and outputs in the network.

- One to One
- One to Many
- Many to One
- Many to Many

3.2.2.1 ONE TO ONE

This type of RNN behaves the same as any simple Neural network it is also known as Vanilla Neural Network. In this Neural network, there is only one input and one output.

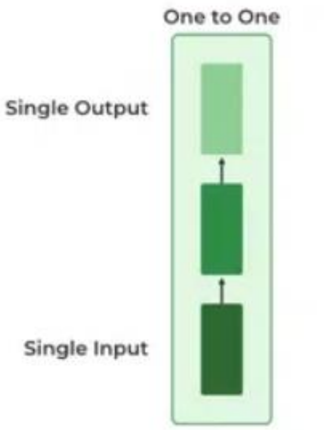


Figure 10: One to one RNN

Source (geeksforgeeks.org, 2024)

3.2.2.2 ONE TO MANY

In this type of RNN, there is one input and many outputs associated with it. One of the most used examples of this network is Image captioning where given an image we predict a sentence having Multiple words.

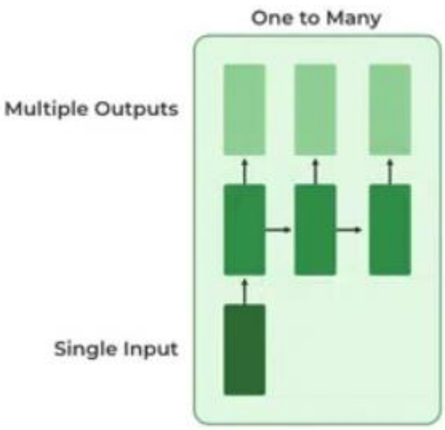


Figure 11: One to Many RNN

Source (geeksforgeeks.org, 2024)

3.2.2.3 MANY TO ONE

In this type of network, Many inputs are fed to the network at several states of the network generating only one output. This type of network is used in the problems like sentimental analysis. Where we give multiple words as input and predict only the sentiment of the sentence as output. (geeksforgeeks.org, 2024)

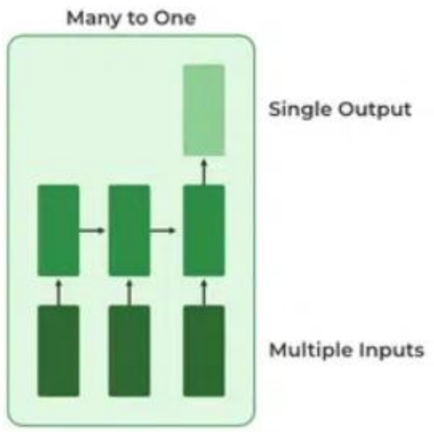


Figure 12: Many to One RNN
Source (geeksforgeeks.org, 2024)

3.2.2.4 MANY TO MANY

In this type of neural network, there are multiple inputs and multiple outputs corresponding to a problem. One Example of this Problem will be language translation. In language translation, we provide multiple words from one language as input and predict multiple words from the second language as output. (geeksforgeeks.org, 2024)

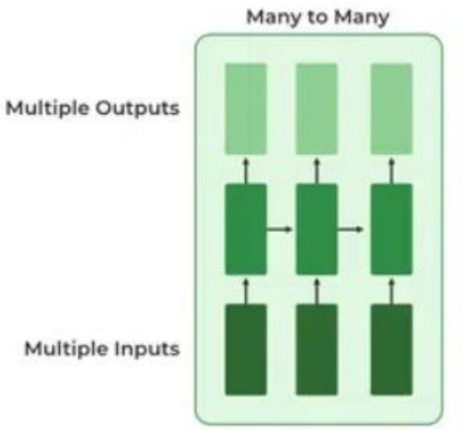


Figure 13: Many to many RNN

Source (geeksforgeeks.org, 2024)

For the purpose of this research project, the Feedforward Artificial Neural Network will be used to train, validate and test data.

3.3 THE RESEARCH STRATEGY

The research strategy for simulation using a Feedforward Artificial Neural Network for optimizing the Nigerian Power Grid will involve the following steps.

1. Gather data about the system to be simulated.

2. Choose an artificial neural network architecture that is appropriate for the problem.

3. Train the network on the data.

4. Use the network to make predictions or optimize the system.

Artificial Neural Networks can be a powerful tool for simulation. They can be used to learn complex relationships between input and output data and to make predictions about new data. However, it is important to carefully evaluate the performance of the network before using it for simulation.

3.4 THE RESEARCH METHOD

This research project simulated a Feedforward Artificial Neural Network for optimizing the Nigerian Electric Power Grid using the Levenberg-Marquardt Algorithm with the aid of MATLAB software.

3.5 THE RESEARCH APPROACH

The research approach of simulating an Artificial neural network involves using a computer program to create a model of the network. The model is made up of a series of interconnected nodes, each of which represents a neuron in the network. The nodes are connected to each other by links, which represent the synapses between neurons. The model is then trained by feeding it a series of inputs and outputs. The inputs are the data that the network is expected to learn, and the outputs are the expected results. The network is adjusted during training so that it learns to produce the correct outputs for the given inputs.

3.6 METHOD OF DATA COLLECTION

Data was collected through the Daily Broadcasts published by the Transmission Company of Nigeria(TCN).

3.7 SELECTION OF THE SAMPLE

The sample data selected from the TCN Daily Broadcast represent the Frequency measured in Hertz(Hz) and Voltage in Kilovolts(kV) recorded as critical parameters causing emergency power outages on a 330kV Transmission line. This spanned a period from 4th January 2024 to 24th January 2024 amounting to over 12,000 units of data.

3.8 TYPE OF DATA ANALYSIS

The model deployed engages quantitative analysis in analyzing the data supplied.

3.8.1 MATHEMATICAL PRINCIPLES

In a Feedforward Artificial Neural Network, mathematical operations are in two steps.

3.8.1.1 THE WEIGHTED SUM OF INPUTS

Each input is multiplied by a weight, and the results are added together with a bias. Mathematically, this can be written as

Weighted sum = $\sum(weights \times inputs) + bias$ -------------(Eqn. 1)

3.8.1.2 THE ACTIVATION FUNCTION

Once the weighted sum is calculated, the output is fed into an activation function, which serves the crucial role of introducing non-linearity to the neuron's output. Non-linearity enables the network to simplify complex functions. Some common activation functions include:

- Sigmoid Function:

$$\sigma(z) = \frac{1}{1+e^{-z}}$$ --(Eqn. 2)

- Hyperbolic tangent (tanh):

$$\sigma(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$$ ---(Eqn. 3)

- Rectified Linear Unit (ReLU):

$$\sigma(z) = \max(0, z)$$ ---(Eqn. 4)

- Softmax (for output layer in classification tasks):

$$\sigma(z) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$ ---(Eqn. 5)

The activation function chosen for in this Feed Forward Artificial Neural Network is the Sigmoid function illustrated in Eqn.2.

A basic illustration of how a Feed forward Artificial Neural Network works is given below.

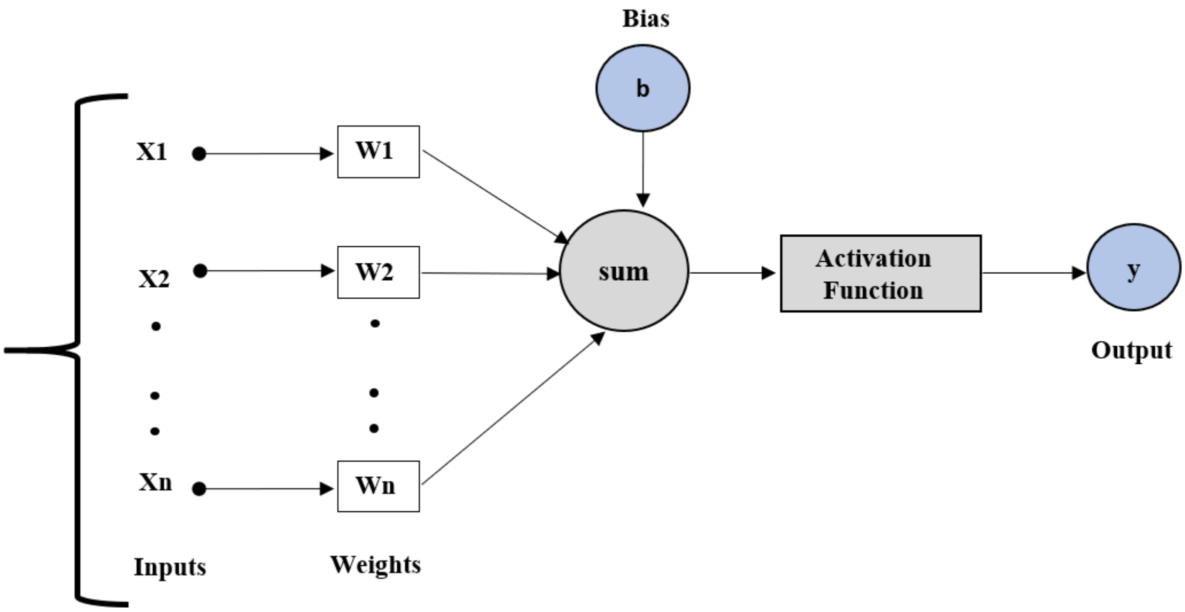


Figure 14: Working Principle of a Feedforward Artificial Neural Network

3.8.1.3 THE LOSS FUNCTION

The loss function measures the difference between the predicted output and actual output of the network. It quantifies the network's performance during training. Common loss functions include mean squared error (MSE) for regression tasks and cross-entropy loss for classification tasks.

3.9 SIMULATION PROCESS

Given below is an illustration of the simulation process of a Feedforward Artificial Neural Network using MATLAB Software.

3.9.1 NETWORK ARCHITECTURE

The diagram below shows the Architecture of the Feedforward Artificial Neural Network showing

- the two data inputs,
- ten neurons contained in the hidden layer
- one neuron connecting to the output layer
- the output

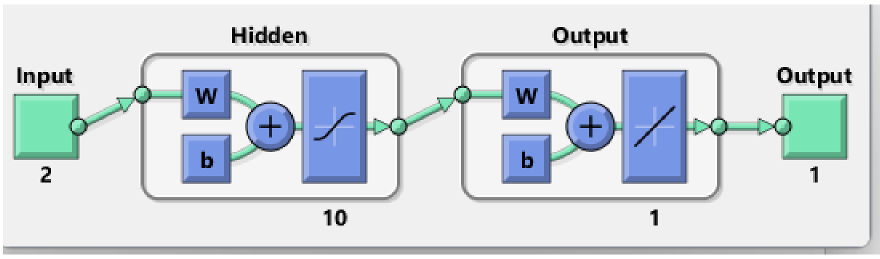


Figure 15: Diagram showing the Architecture of the Artificial Neural Network

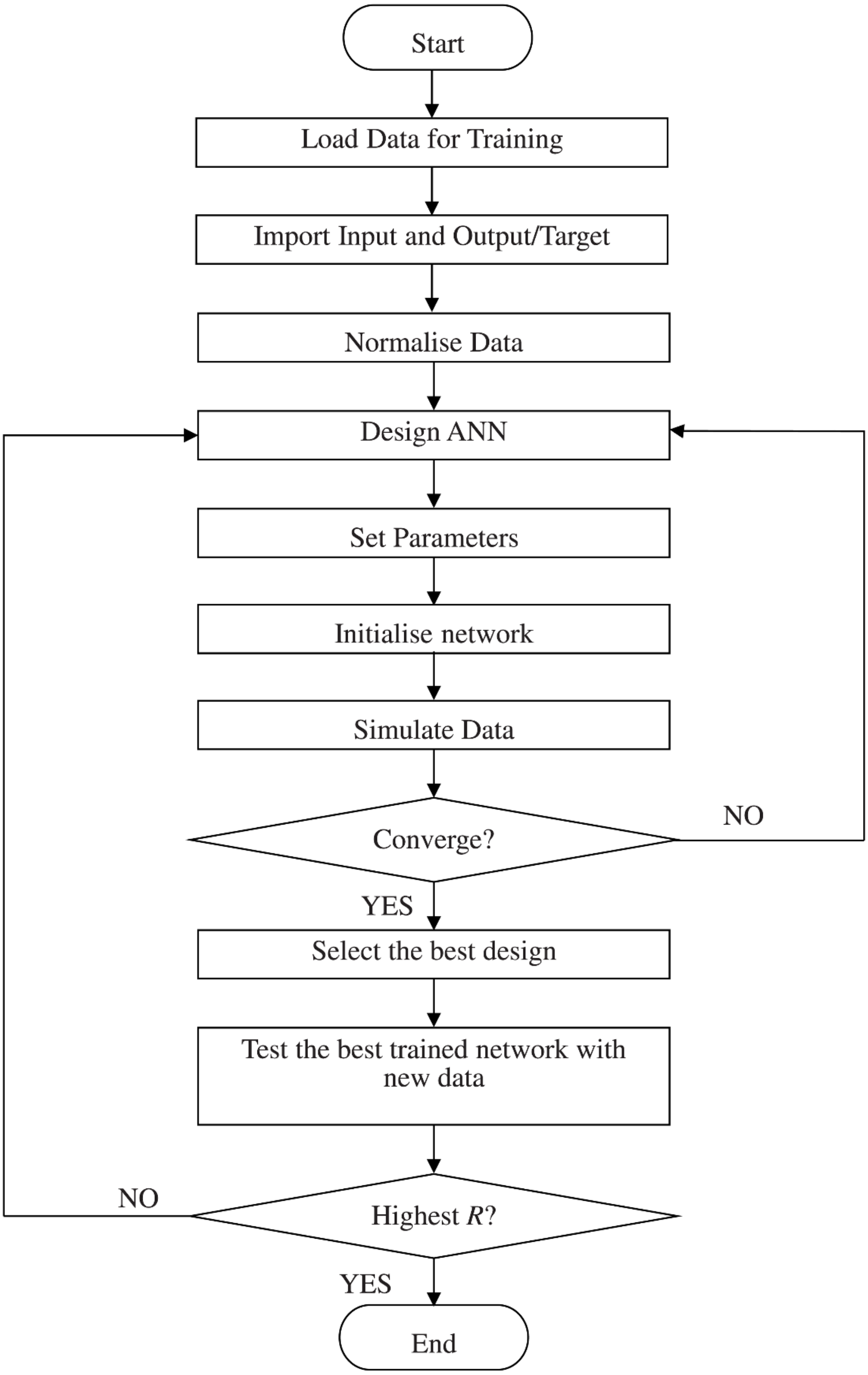


Figure 16: Flowchart of Artificial Neural Network

Source:https://plos.figshare.com/articles/figure/_Flowchart_of_ANN_algorithm_/146
1285

3.9.2 TRAINING OF THE ARTIFICIAL NEURAL NETWORK

Training an artificial neural network (ANN) involves the process of adjusting its parameters (weights and biases) so that it can perform a specific task effectively. This process typically involves presenting the network with a set of input data along with the corresponding correct outputs (targets), known as the training data. During training, the network makes predictions based on the input data, compares these predictions to the targets using a loss function to measure the difference, and then adjusts its parameters using optimization algorithms (such as gradient descent) to minimize this difference. This iterative process continues until the network's predictions closely match the desired outputs for a wide range of input data, indicating that it has learned to perform the task effectively.

In other words, training an Artificial Neural Network involves using a particular fitting algorithm to set the input parameters to align to a particular target output.

The process starts with calling up the Neural Net Fitting tool in MATLAB by typing **nftool** in the command window as shown below.

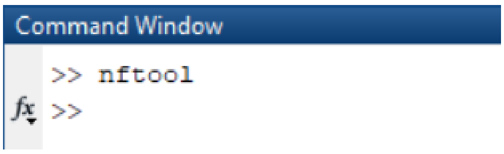


Figure 17: Figure showing neural network fitting tool being called up

This leads to the following interface which introduces the working principle of the MATLAB Neural fitting application.

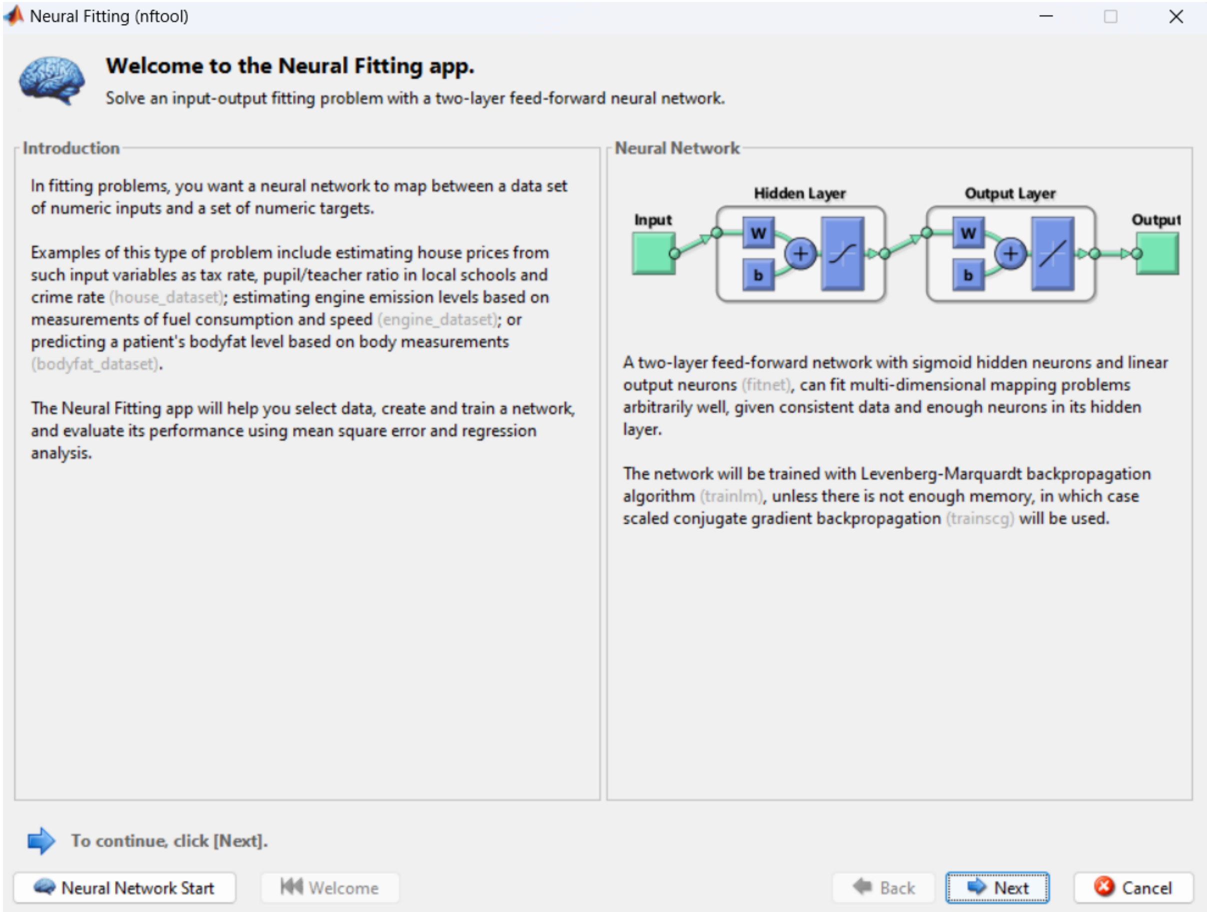


Figure 18: Figure showing neural network fitting tool being called up

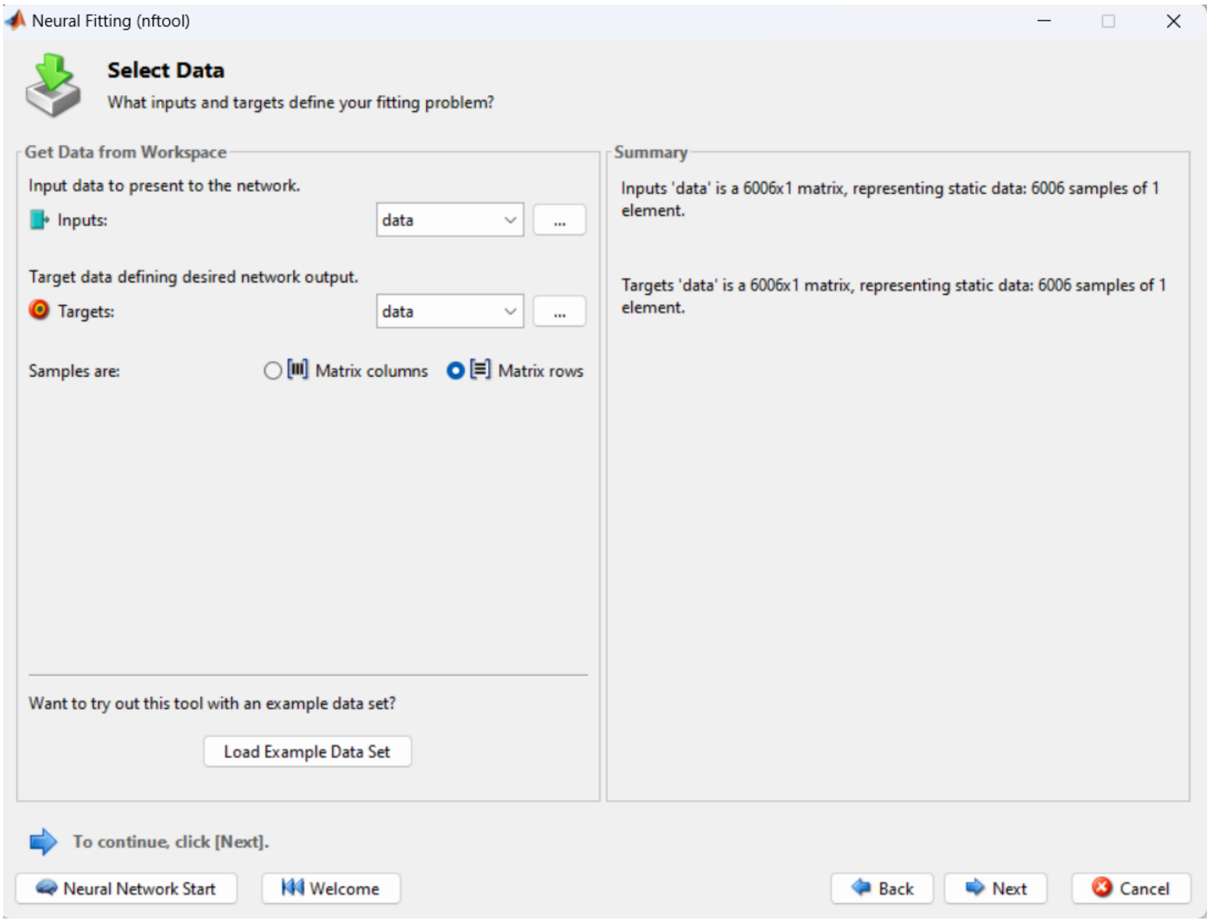


Figure 19: Interface for input and target data selection

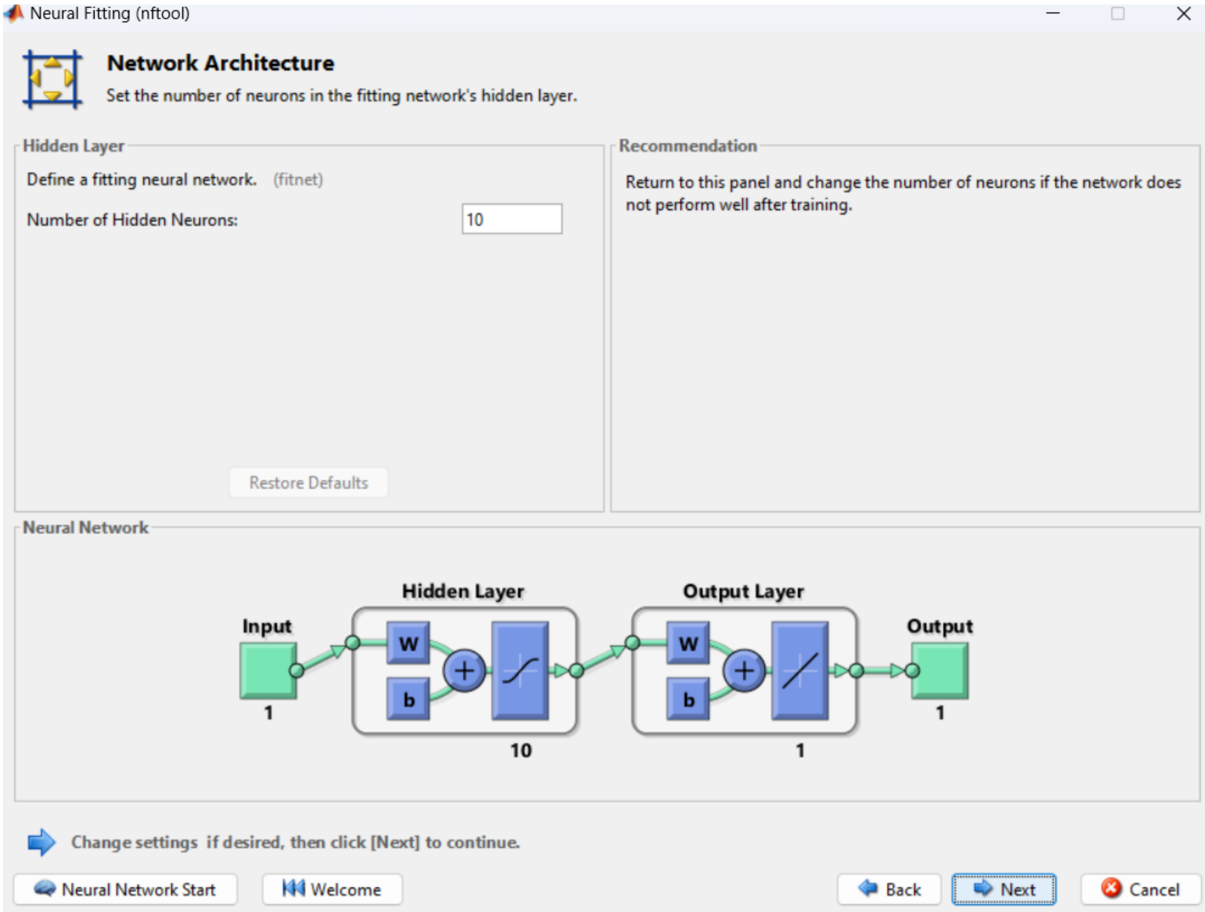


Figure 20: Figure showing the number of neurons selected for this model

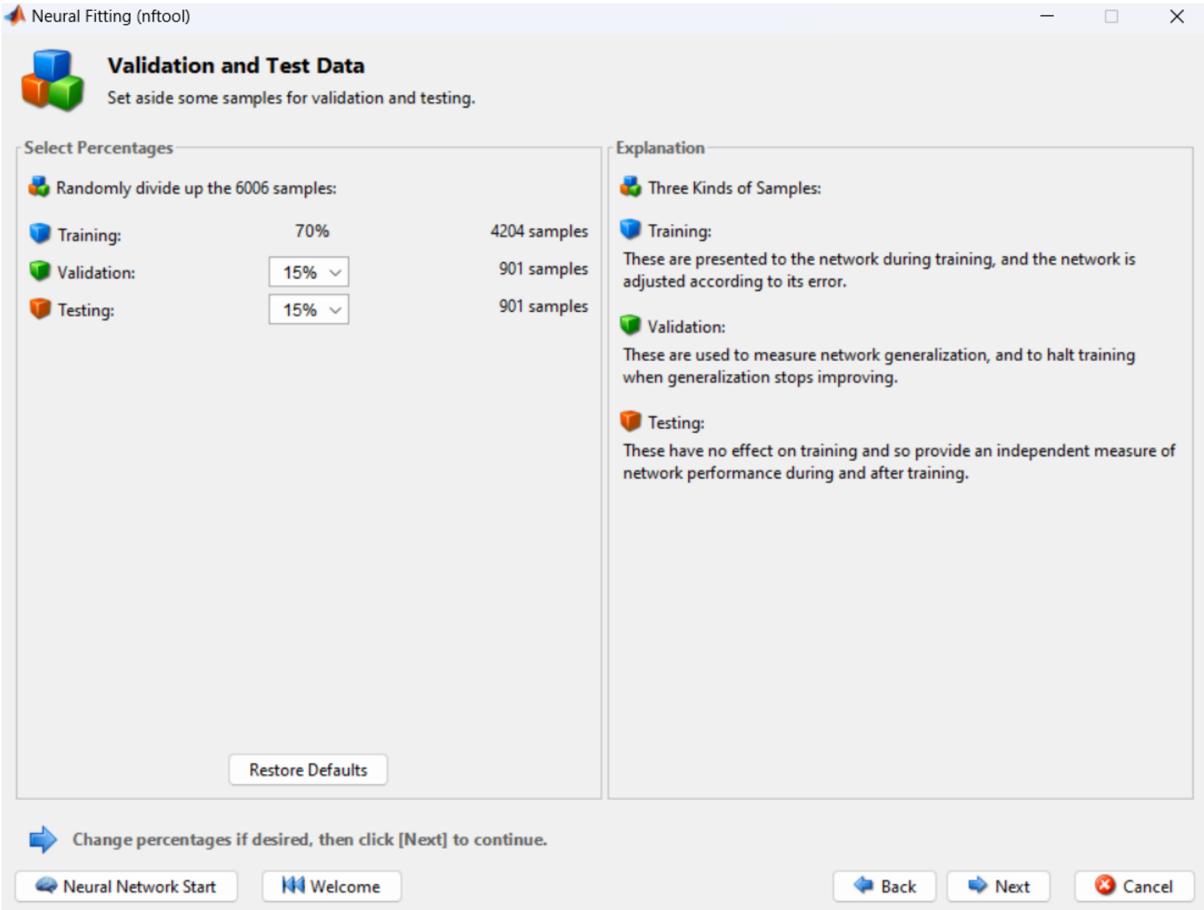


Figure 21: Figure showing training, validation and testing data partitioned

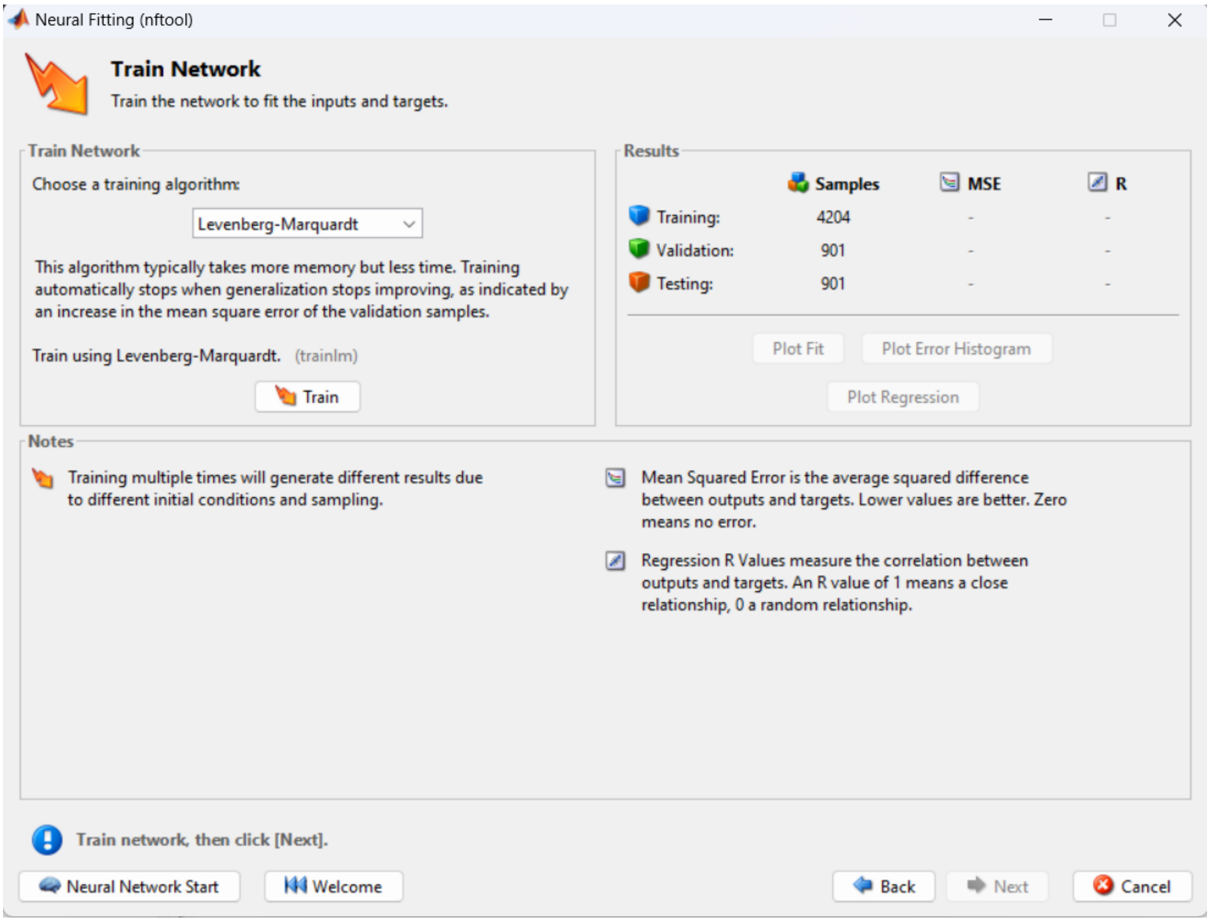


Figure 22: Image showing interface before Network training using the Levenberg-Marquardt Algorithm

Figure 23: Showing the training, validation and testing interface

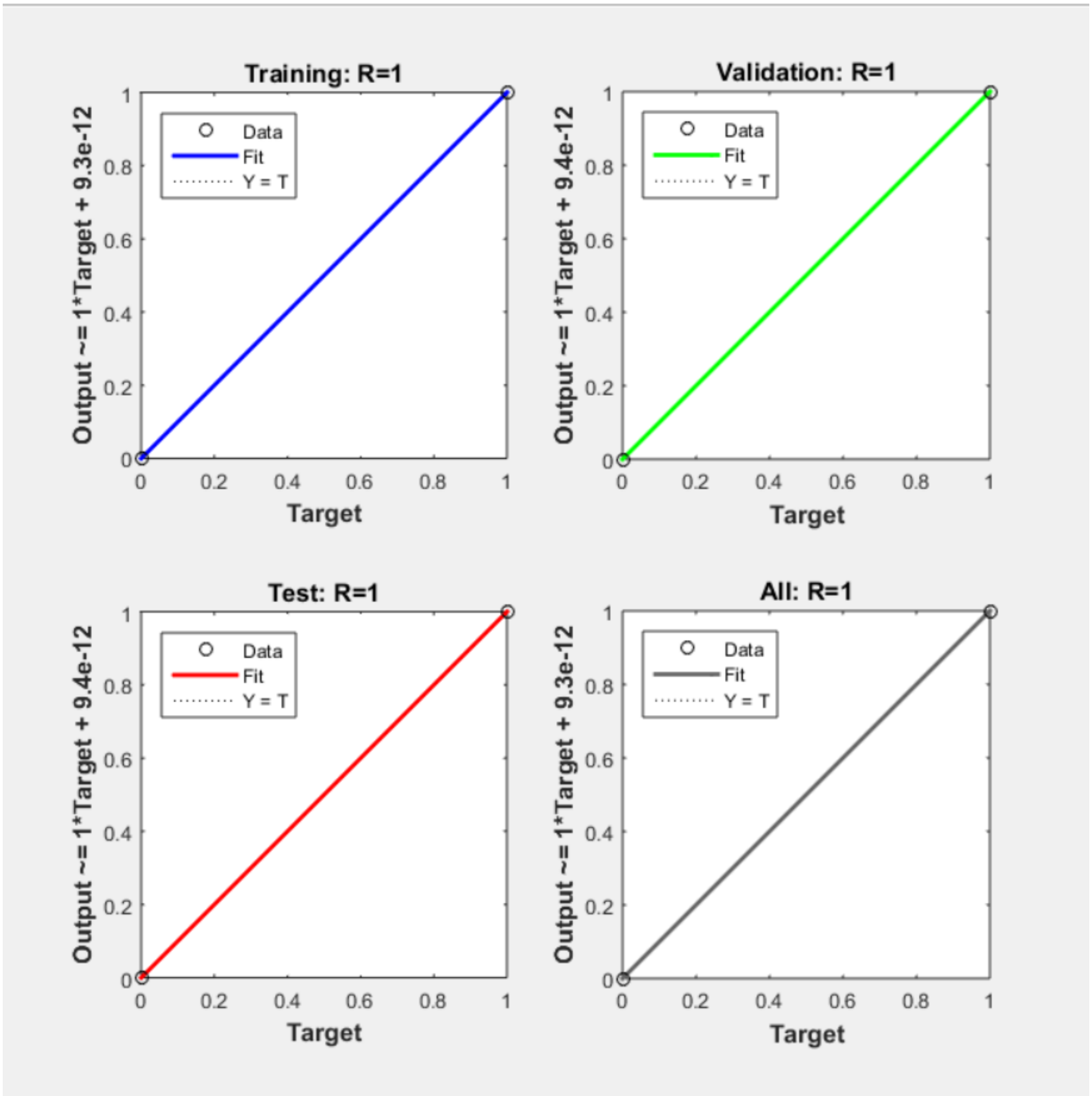


Figure 24: Plot showing curve fitting for training, validation and testing

3.10 PRECAUTIONARY CONSIDERATIONS

It is important to note that artificial neural networks are not perfect. They can be prone to overfitting and bias. It is therefore important to carefully evaluate the performance of the network before using it for simulation.

3.11 RESEARCH LIMITATIONS

The following were limitations encountered during this research.

1. Limited access to available data
2. Lack of equipment/laboratory
3. Limited time

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 INTRODUCTION

This chapter basically outlines the results obtained and discussions following the results in this research project.

4.2 TEST PLAN

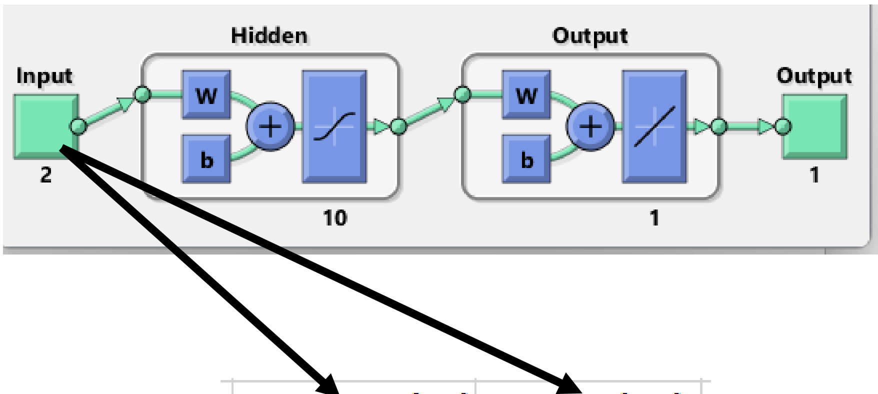
As stated earlier, the research strategy for simulation using a Feedforward Artificial Neural Network for optimizing the Nigerian Power Grid involved the following steps.

4.2.1 INPUT DATA

The sample data selected from the TCN Daily Broadcast represent the Frequency measured in Hertz(Hz) and Voltage in Kilovolts(kV) recorded as critical parameters causing emergency power outages on a 330kV Transmission line. This spanned a period from 4th January 2024 to 24th January 2024 amounting to over 12,000 units of data.

Hence, the input data to be fed into the Artificial Neural Network comprises of two parameters which are (1) Frequency (measured in Hz) and (2)Voltage in Kilovolts.

This is illustrated as follows with a few sample data.



Frequency(Hz)	Voltage(kV)
49.45	312.23
49.47	335.68
49.46	299.32
49.37	288.31
49.42	333.18
49.12	334.67
49.11	332.16
49.16	315.98
49.96	302.20
49.79	297.17
49.92	320.83

Figure 25: Showing the input data being fed into the Artificial Neural Network.

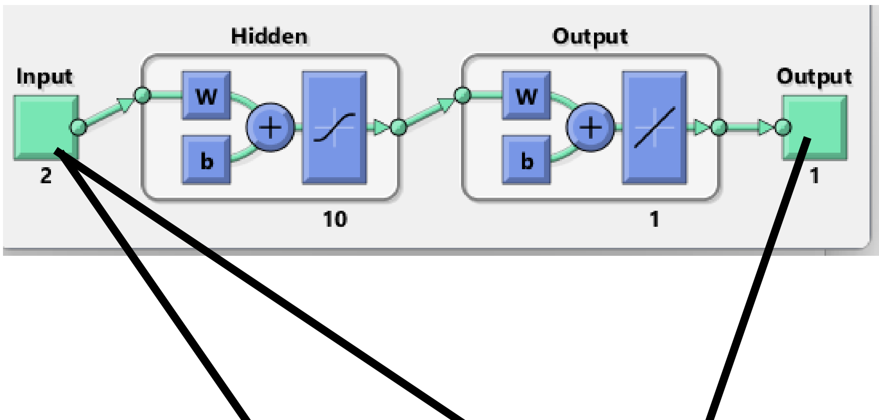
4.2.2 ASSUMPTIONS MADE ON THE OUTPUT END

Because of the accuracy desired from the quantitative analysis of the data gathered from the power grid, we use zero(0) to represent a power outage or 'power off' state on the grid and one(1) to represent 'power on' state on the grid at the target end or output.

Each row on the input end corresponds to a target on the output end. The inputs and their corresponding outputs are a representation of the critical frequency and voltage levels that result in power outages on the 330kV Transmission lines.

As stated in chapter one, there is a standard operating frequency and standard operating voltage for the Nigerian National Grid. For frequency, 50Hz is the standard operational value with tolerance of +/-0.5% (49.75 – 50.25 Hz), but under System Stress the Frequency on the Power System could experience variations within the limits of 50 Hz +/- 2.5% (48.75 – 51.25 Hz). While for voltage on a 330kV line, a tolerance of -15% (280.5kV) and +5% (346.5kV) is acceptable.

Any violation of the set standards could lead to power outages and ultimately a grid collapse under prolonged circumstances. The input values given in figure 25 above and their corresponding target output values are given below.



Frequency(Hz)	Voltage(kV)	Grid Status
49.45	312.23	0
49.47	335.68	0
49.46	299.32	0
49.37	288.31	0
49.42	333.18	0
49.12	334.67	0
49.11	332.16	0
49.16	315.98	0
49.96	302.20	1
49.79	297.17	1
49.92	320.83	1

Figure 26: showing the input data and corresponding target output on the grid

4.2.3 TRAINING AND VALIDATION OF THE FEEDFORWARD ARTIFICIAL NEURAL NETWORK

The Feedforward Artificial Neural Network was trained with the Levenberg-Marquard Algorithm using over Eighteen thousand (18,000) cells of data. This comprises of the input data - frequency(Hz), voltage(kV)) and the target output (representing the grid status) arranged in the same manner as in figure 26.

The data samples for Training, Validation and Test are randomly divided in the following manner.

- **Training data** is presented to the feedforward artificial neural network during the network’s training. During this stage, data samples are gathered for the purpose of "teaching" or "training" the machine learning model. Through the use of a training data set, the model gains an understanding of the patterns and relationships present in the data, enabling it to make predictions and judgments without the need for explicit task programming.
- **Validation data** is used to measure the effectiveness of the training model and to make further improvement on the model. Various samples are included in validation datasets to assess trained machine learning models. At this point, the model can still be adjusted and controlled. Analyzing validation data is a useful tool for evaluating model performance and optimizing model parameters. The model learns from the training set and is subsequently validated and improved upon on the validation set in an iterative process. A validation dataset provides information on how successfully the model is learning and adapting, enabling fine-tuning and optimization of the model's parameters or hyperparameters prior to its ultimate testing.

Table 2: Proportions of Training, Validation and Test data

Training	70%
Validation	15%
Testing	15%

4.2.4 TESTING THE FEEDFORWARD ARTIFICIAL NEURAL NETWORK

An unbiased final assessment of a model fit is provided by a **test data set**, which is an independent sample of previously unseen data. While not identical, the test data's inputs are comparable to those from earlier phases. The machine learning model is exposed to real-world data for the first time through the test data set. Its main goal is to provide an objective and comprehensive evaluation of the model's performance in the event of new data in an operational, real-world setting.

4.3 RESULTS

It was observed that the performance of the Feedforward Artificial Neural Network improves with multiple iterations. Hence, the network was trained over and over again to get the best result.

The best result with the least Mean Squared Error(MSE) and most acceptable Regression value(R) is presented as follows.

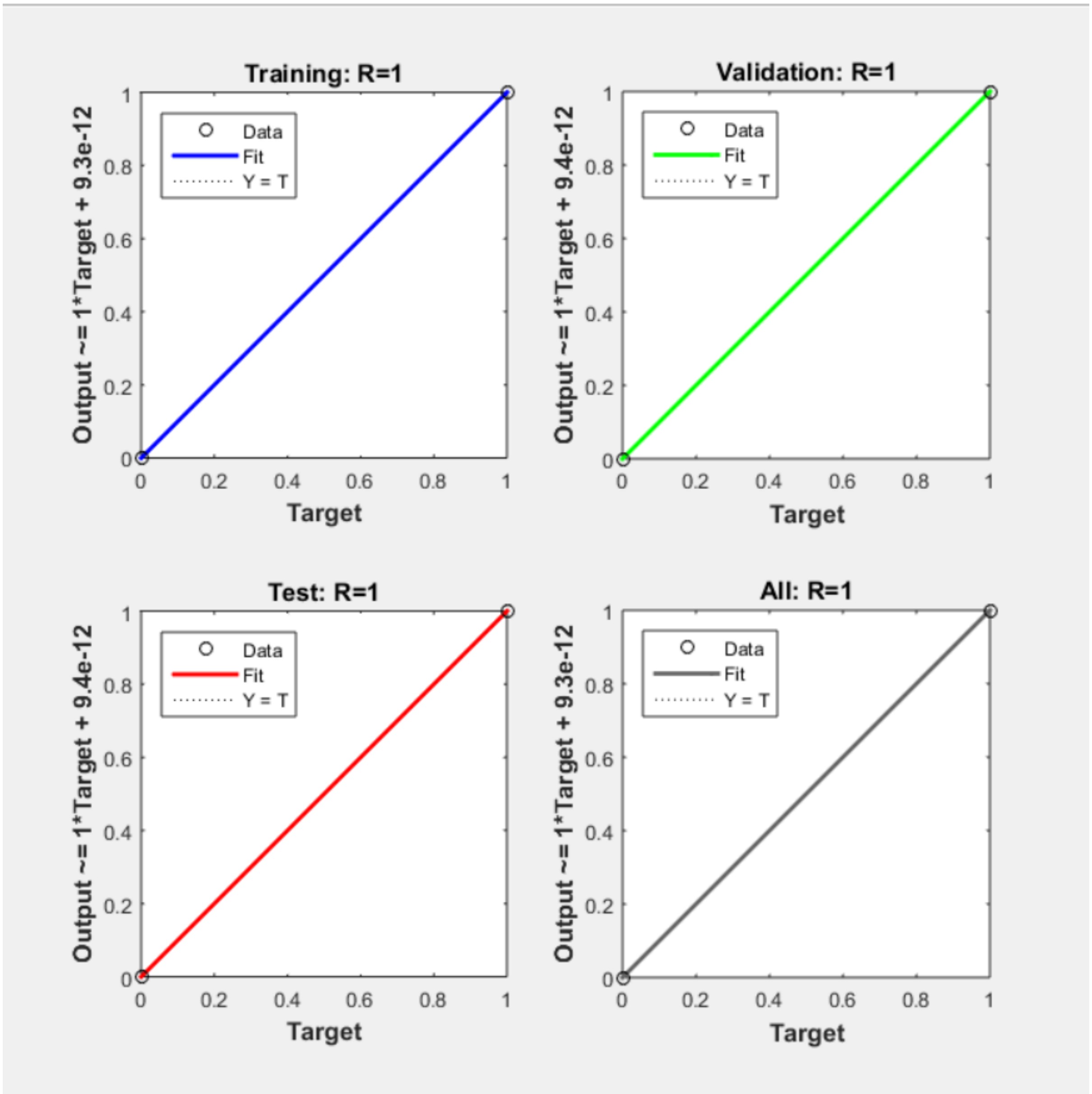


Figure 27: Regression plot for Neural Network for Training, Validation and Testing

Results

	Samples	MSE	R
Training:	4204	1.90935e-24	1.00000e-0
Validation:	901	1.62409e-24	1.00000e-0
Testing:	901	1.75707e-24	9.99999e-1

Figure 28: Showing MSE and R for Training, Validation and Testing data

Figure 27 above represents the regression plot for training, validation and testing. The Regression value, R, suggests that the independent variables (Frequency and Voltage) together can explain/determine 100% change in the dependent variable (Grid status).

4.3.1 TEST RESULTS

Below is the result for the test data supplied to the network.

Table 3: Test input data

Frequency(Hz)	Voltage(kV)
50	330
49.8	331
43.48	291.21
43.68	323.39
41.55	289.84
44.92	281.81
45.20	312.32
44.41	321.29
48.87	313.82
43.28	288.42
48.43	292.18
47.40	309.25

```
Command Window

  Columns 1 through 10

    1.0014    1.0014    0.0011    0.0011    0.0011    0.0011    0.0011    0.0011    0.0011    0.0011

  Columns 11 through 12

    0.0011    0.0011

fx >>
```

Figure 29: Output result of the test data supplied to the network

The test result above clearly validates the efficiency of the trained Feedforward Artificial Neural Network in that the network clearly predicts the status of the power grid when supplied the input values of Frequency(Hz) and Voltage(kV). The standard operating values released by NERC for frequency and voltage on a 330kV line was earlier given in chapter 1.

It can be observed clearly that the first two values on the test input data (Frequency and voltage) are within the standard operating values while the rest do not fall within standards. This is clearly corresponding with the expected target output in that the first two values of the output result suggest the presence of power supply on the grid while the rest of the values suggest power outage on the grid. Remember in this simulation, '1' on the grid represents 'power on' state of the grid or the presence of power supply while '0' represents 'power off or power outage' on the grid.

4.4 DISCUSSION

The intent of this research is the implementation of a Feedforward Artificial Neural Network for optimizing the Nigerian Electricity Grid. Having trained a functional

Neural Network to model the behaviour of the Nigerian Electricity Grid under certain conditions, the model can be further optimized through Time-Series Modelling.

Time series forecasting models are used to forecast or to predict the future value over a period of time. Such models are developed based on previous data and are applied to make observations.

With the possibility of making predictions comes the opportunity for making informed and guided decisions on practical steps to take in order to prevent future undesirable occurrences on the Nigerian Electricity Grid.

4.5 COHERENCE WITH OTHER ACADEMIC WORKS

The deductions and generalizations mentioned above converges with those of (Abdolsarol, et al., 2021). In their research titled "Artificial Neural Networks Based Optimization Techniques: A Review", they highlighted that "using an Optimization Algorithm in place of Back-Propagation, like using the Liebenberg Marquardt Neural Network with any Optimization technique arrives at fast or accurate result in the Neural Network Training". Their research further reviewed "highlights improving the Neural Network by optimizing algorithms by handling Neural Network parameters or training parameters". This they did to find the finest structure network pattern to solve the problems with high accuracy and speed. This review included testing results for improving the ANN performance using four Optimization Algorithms to search for ANN's optimal parameters, such as the number of neurons in the hidden layers and learning rate. The obtained neural net is used for solving energy management problems in a virtual power plant system.

CHAPTER FIVE

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

5.1: SUMMARY

The Nigerian Electricity Industry is currently facing a lot of challenges ranging from frequent power outages to series of collapses in the entire Electricity Grid. These are attributed to

- Gas Constraints
- Changes in water level
- Power line constraints
- Aged and Faulty Equipment
- Frequency control issues
- Voltage control issues
- Absence of a functional SCADA System/Smart grid

This research project seeks to improve the situation of the Nigerian Electricity grid by optimizing the system using a Feedforward Artificial Neural Network. This will be done by first modeling the behaviour of the grid using some features. These features are Frequency and Voltage. They are the independent variables which will be used to determine the output or target expected.

In order to achieve this,

- The best algorithm to solve an Input-Output Fitting problem using an Artificial Neural Network was found. The training algorithm used was the Levenberg-Marquardt Algorithm.
- Training Data was collected through the Daily Broadcasts published by the Transmission Company of Nigeria(TCN).

- Using the data collected we created a Feedforward Artificial Neural Network which has two(2) inputs, ten (10) neurons, and one(1) output.
- The Artificial Neural Network was trained using the sample training data.
- We tested the Feedforward Artificial Neural Network with New Sample Test Data to affirm the effectiveness and efficiency of the Network.

Therefore, a functional Feedforward Artificial Neural Network was trained to model the behaviour of the Nigerian Electric power grid under certain conditions using the Levenberg-Marquardt training Algorithm.

This research project was divided into five(5) main chapters:-

CHAPTER ONE

This chapter presents a background of the research project, some examples of Artificial Intelligence, problem statement, objectives of this research project, justification, and scope of this research project.

CHAPTER TWO

In chapter two, an attempt was made to review the state of play (literature review) of the existing body of knowledge in Artificial Intelligence and Machine learning. A discussion of the various applications of Artificial Intelligence and Machine Learning was also presented.

CHAPTER THREE

Chapter three presented the Methodology of this research project. Here a Feedforward Artificial Neural Network was created and suitable algorithm was chosen to simulate the Training, Validation, and Testing of the Network.

CHAPTER FOUR

This chapter basically presents an outline of the observations and results recorded in the research project.

CHAPTER FIVE

Chapter five presents a summary, conclusion and recommendations, and knowledge added through this research project.

CONCLUSION

The results of this research project show that the Feedforward Artificial Neural Network can be successfully applied to the optimization of Electric Power Grids. Here are a few benefits which can be derived from using Feedforward Artificial Neural Networks in the Nigerian Electric Power Grid.

- Frequency and Voltage values can easily be used to forecast the Performance of the Nigerian Electricity Grid.
- Predictive analytics
- Load forecasting
- Time-series modelling

RECOMMENDATION

It is therefore recommended that the model developed be adopted into the Nigerian power sector in order to optimize and improve the Electric power grid as this model has the potential for expanded applications in Predictive Analytics, Load Forecasting, and Time-Series modelling.

KNOWLEDGE ADDED

In this research project, a Feedforward Artificial Neural Network model has been developed and successfully applied to Enhancing Fault Detection and Diagnosis as a step towards improving the Nigerian Electric Power Grid.

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GLOSSARY

AI – Artificial Intelligence

ANN – Artificial Neural Network

ASC – Agriculture Supply Chain(s)

ASR – Automatic Speech Recognition

DL – Deep Learning

Hz – Hertz

IBM – International Business Machines

IEA - International Energy Agency

IEEE – Institute of Electrical Electronic Engineers

IoT – Internet of things

IT – Information Technology

kV – Kilovolts

MATLAB – Matrix Laboratory

ML – Machine Learning

MoA – Mechanism of Action

MSE - Mean-Squared-Error

NERC – Nigerian Electricity Regulatory Commission

Nftool – Neural Network Fitting Tool

NLP - Natural Language Processing

NN – Neural Network

PdM – Predictive Maintenance

PVM – Preventive Maintenance

R - Regression value

R&D – Research and Development

R2F – Run to Failure

RFID – Radio Frequency Identification

RNN – Recurrent Neural Network

SAP – Sustainable Agriculture Practice(s)

TCN – Transmission Company of Nigeria

UK – United Kingdom