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FAULT PREDICTION IN RENEWABLE ENERGY BASED SMART ELECTRIC GRID USING ARTIFICIAL INTELLIGENCE

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Master's Thesis

Supervisor

Asst Prof. Dr. Sefer KURNAZ

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The thesis titled FAULT PREDICTION IN RENEWABLE ENERGY BASED SMART ELECTRIC GRID USING ARTIFICIAL INTELLIGENCE prepared MSHHAIN GHAZI ABDULAZEEZ and submitted on 08/08/2023 has been **accepted unanimously** for the degree of Master of Science in Electrical and Computer Engineering.

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I hereby declare that this thesis meets all format and submission requirements of a Master’s thesis.

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

Mshhain Ghazi ABDULAZEEZ

Signature

DEDICATION

Before I continue, I want to praise and thank Allah, the Almighty, for giving me the knowledge, abilities, and opportunity to carry out and successfully complete my research. My parents have my sincere thanks. Everything wonderful that has happened to me has been motivated by them, and their love is the energy that enables this to be the case. I'd like to end by thanking my sister and brother for their support and affection during this process.

PREFACE

My advisor, Asst. Prof. Dr. Sefer KURNAZ, deserves a lot of credit for giving me the guidance, supervision, encouragement, and help I needed to finish my study. His willingness to collaborate with me, persistence, constructive criticism, and useful suggestions have greatly boosted my understanding and confidence. I value the time he spent reviewing my work and pointing out my mistakes. Last but not least, I would like to express my gratitude to everyone who helped in any way, whether it was by offering support, prayers, or useful advice.Thanks.

ABSTRACT

FAULT PREDICTION IN RENEWABLE ENERGY BASED SMART ELECTRIC GRID USING ARTIFICIAL INTELLIGENCE

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The concept of intelligent energy networks (Intelligent Energy Networks), or Smart Grid (SG) has been developed aiming to make the EPS operation more robust, economical, reliable, available and automated. New technologies, applications and smart devices have been developed, mainly to make the distribution layer smarter. However, an EPS must have an integrated intelligent operation, aggregating all functionalities at all levels of the EPS with the aim of improving the EPS's performance in terms of economics, quality of service and technology. The use of these resources makes it possible to make the operation of the electrical system more flexible in the contexts of generation, transmission and distribution, reaching new levels of quality for these services. One of the main impacts that EPS have on current systems is in the context of energy generation The objectives of this work are to analyze and develop methods for predicting energy demand and supply in an SG in the context of Smart Grids

Keywords: EPS, EMS, AI, SG, IEN.

TABLE OF CONTENTS

Pages

LIST OF TABLES

<u>Pages</u>

LIST OF FIGURES

ABBREVIATIONS

EPS	:	Electrical Power System
SG	:	Smart Grid
SEG	:	Smart Energy Grids
DES	:	Distributed Energy Sources
ML	:	Machine Learning
AI	:	Artificial Intelligence

1. INTRODUCTION

1.1 INTRODUCTION

The electrical power system (EPS) is one of the largest systems ever produced by man - the large national interconnected systems operate with powers in the order of billions of people. The intensive use of electricity in modern life and society implies a growing demand and the need for ever higher reliability of generation, transmission and distribution systems. From the development of new sensing, control, supervision and operation components applicable to generation plants and networks, it becomes possible to optimize the operation of the EPS: the system as a whole now contains components capable of acting autonomously or remotely controlled and, in addition, generates data that can be used online in its supervision and control [1].

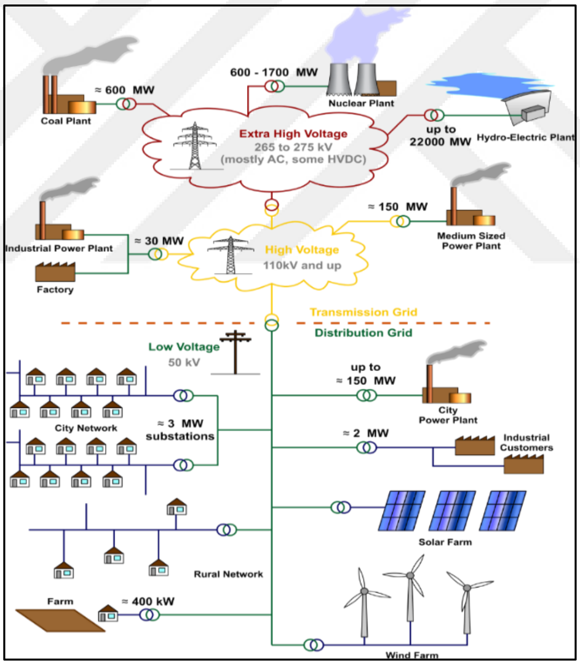

Figure 1.1: Basic Scheme of the Current EPS [1].

The classic EPS is formed from the layers of generation, transmission and distribution subsystems. Figure 1.1 illustrates the unidirectional flow that energy assumes in this system. In the current scenario, generation is made up of generating parks with large installed capacity. Primary energy sources determine the energy matrix of the country or region where these plants are located. For example, the energy matrix is mainly composed of hydroelectric dams with the presence of thermoelectric plants with the purpose of emergency generation (backup) [2] Nonetheless.

1.2 PROBLEM STATEMENT

It can be seen that sources such as wind and photovoltaic sources have been occupying more and more space in the energy matrix. Currently, these sources account for approximately 2.7% of the national installed capacity. This scenario tends to be expanded as:

a. The distribution concessionaires adapt to receive distributed generation (Distributed Generation) by implementing the grid code [3]
b. The cost of the equipment needed for integration that this Distributed Generation becomes more accessible to the prosumer [4] (spelling assumed from now on as "prosumer" [5]
c. There is a free market in which energy can be negotiated between the various agents involved.

The electrical energy distribution system comprises mainly the network with voltages below 13.8 kV, fed by substations, and the step-down transformers that will adjust the voltage for the final consumer to 127 V, 220 V or 380 V depending on the region and the standardization of the concessionaire [6] This system has a very high capillarity and is where the main points of improvement for energy quality and reliability are located.

The concept of intelligent energy networks (Intelligent Energy Networks), or Smart Grid (SG) [7] has been developed aiming to make the EPS operation more robust, economical, reliable, available and automated. New technologies, applications and smart devices have been developed, mainly to make the distribution layer smarter. However, an EPS must have an integrated intelligent operation, aggregating all functionalities at all levels of the EPS with the aim of improving the EPS's performance in terms of economics, quality of service and technology. The use of these resources makes it possible to make the operation of the electrical system more flexible in the contexts of generation, transmission and distribution, reaching new levels of quality for these services. One of the main impacts that EPS have on current systems is in the context of energy generation. There are often opportunities for generation on a smaller scale and distributed throughout the EPS. A classic example are the cases of generation by photovoltaic panels (which can even be installed in buildings, see Figure 1.2), generation by wind energy and cogeneration. This energy generated at the opposite end of the system could be sold to other consumers as soon as appropriate converters and energy meters are integrated into the EPS.

Figure 1.2: Installation of a Photovoltaic System in a Residential Building [8].

An EPS must be able to carry out the purchase and sale operations of this energy from distributed sources in the form of direct negotiation between consumer and producer agents or by aggregating generation in virtual plants [8] Inverters and meters must communicate with each other and with other agents within the EPS environment so that the exchange of information implies the determination of market parameters such as a) the amount of energy that the system is willing to receive, b) how effectively the producer will earn with the sale of this energy, c) forecast of demand and price curves for energy. A system architecture with this flexibility allows the expansion of distributed generation while maintaining economic sustainability [9]. Large electrical systems often experience stress due to technological and economic bottlenecks. In addition, due to growing concerns about the environmental impacts of energy generation, there is a tendency towards ever greater diversification of the energy matrix, including renewable sources. These sources can be located anywhere along the electrical system, hence the importance of flexibility in integrating them into the system. Another important concern for electrical systems is robustness against external attacks, information security and immunity to natural events. The structuring of an EPS seeks to satisfactorily address all these concerns, generating value for society and the electrical system as a whole.

1.3 THESIS MOTIVATION

EPS are the next technological leap to be achieved for energy generation, transmission and distribution systems, attempts have been made to automate each of these systems to carry out the main services (generation, transmission, distribution) and ancillary services (reactive compensation, fault isolation, alarm triggering, voltage regulation). Electric power concessionaires seek to use, with the best cost-benefit ratio achievable, resources such as telemetry, fault detection, prediction and identification of faults in transformers, fraud detection, phasor measurement, message exchange systems between substations, among others. Others, so that the quality of electricity is maintained and OPEX is minimal.

With recent advances in the fields of distributed and ubiquitous computing and also in telecommunication systems, it becomes possible to add responsiveness to components that would previously only be reactive or commanded in the system. This responsiveness, combined with the coordination between the various other components of the system, makes it intelligent as it is possible to act autonomously to achieve goals in the best human interest.

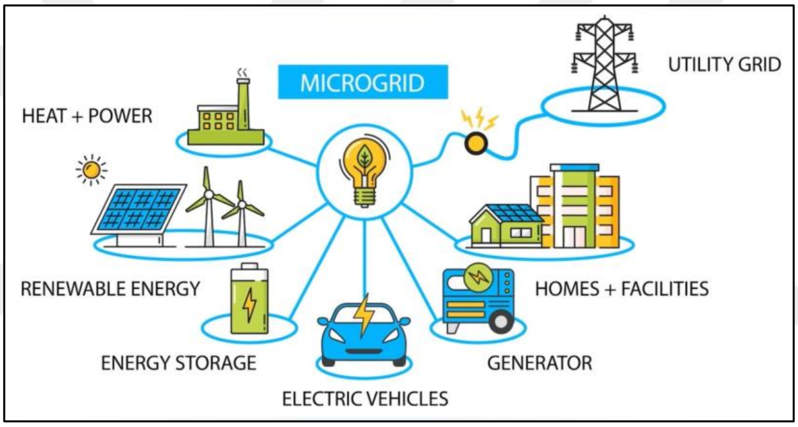

Figure 1.3: Microgrid [9].

The use of intelligent systems in the infrastructure of energy systems will mean progress such as lower technical losses, failure prediction capacity, programmed shutdown capacity and contingency plans, minimizing or nullifying failure rates and downtime. With this, an operation with optimized costs and high reliability is expected. A key component of EPS are microgrids (MR) [9] Figure 1.3 shows the main building blocks of SG, which are demand control, distributed generation (including renewable and non-renewable sources), the presence of accumulators to support ancillary services and the point of interconnection with the main grid (“backbone”). Microgrids can be understood as subsets of the distribution system with the following characteristics:

a. Presence of distributed generation - PV, wind, biomass generation, in prosumers;
b. Islanding capacity - it can be strategic to avoid the effects of a fault external to the MR, or to avoid the propagation of an internal fault or even as an economic decision to avoid

the purchase of energy external to the MR;

c. Presence of telecommunications infrastructure between intelligent components (agents);
d. Strong presence of sensors.
e. Distributed energy sources have some important characteristics, including:
f. Low energy density;
g. Sources limited to a geographic region and close to consumption centers;
h. Stochastic processes in the generation and consumption of energy, with seasonal characteristics of very short cycles.

The stochasticity in the energy generation and consumption processes in SG is an important factor to determine its technical and economic viability [10] Although making predictions about the behavior of the load curve (demand) and the energy supply curve is a common operation in any current Electric Power System (EPS) [11] current prediction methodologies (forecasting) would not be directly applicable to SG, and therefore to EPS. The current EPS are based on large generation systems, with transmission systems that transport large blocks of energy to large consumer poles. Prediction tasks for generation and demand are characterized here by the quasi-stationarity of many of these processes. The microgrids, in turn, have generation and demand physically linked at the same connection point, with the energy source subject to sudden variations by processes as volatile as cloud shading (in photovoltaic generation), or the demand curve very sensitive to variations as as sudden as the activation of a more powerful domestic engine (hydraulic pump for artesian wells, for example). Figure 5 illustrates the sensitivity of the demand curve of a microgrid in the face of a consumer disconnection. It consists of a microgrid with five residential users; the individual curves of customers A, B, C, D, E, the resulting load curve and the impacts of withdrawals from each of the network customers are shown. Considering the generation in the large current EPS, as the large interconnected systems were created, it was necessary to know and predict the behavior of the sources used in the large energy conversion centers in order to carry out energy planning and operation planning. However, the current EPS was structured based on sources with high energy density and greater geographic concentration. The main sources currently used are dams for hydroelectric generation, mineral coal, hydrocarbons (oil, natural gas) and nuclear these sources also show stochastic behavior. However, sources such as hydroelectricity have well-known seasonality periods, while other sources such as hydrocarbons are subject to

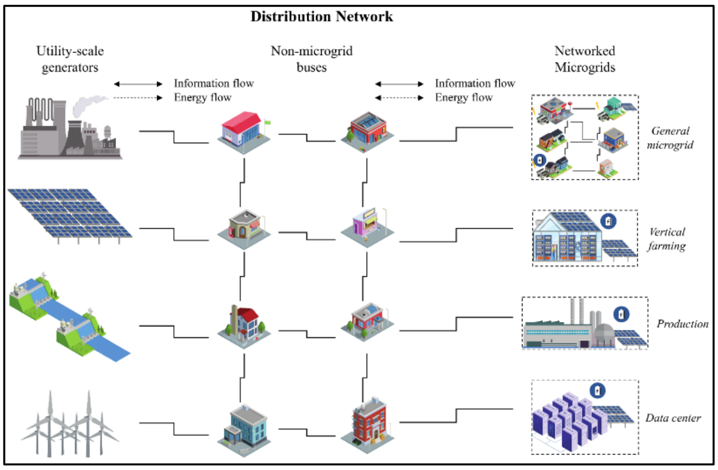

Figure 1.4: Sensitivity of a Microgrid to a Consumer Shutdown [11].

To the laws of supply and demand, thus showing strong trends and weak seasonality. Sources such as nuclear undergo strict governmental and international control by agencies such as the IAEA and Ministries of Defense of countries with this type of generation; therefore, supply of inputs for nuclear generation depends on strong internal and external regulation in each country. This type of knowledge, which must be a priori, provides a greater degree of assertiveness in planning the expansion and operation of interconnected systems. Regarding the demand forecast, by aggregating many demand curves from an entire geographic region, the consumption patterns are better established and therefore the forecast for the total area is less susceptible to variations in the individual load curves. Figure 5 exemplifies the sensitivity of a microgrid to the variation of the load curve of some of its components. In this figure, all values are in pu Taking a hypothetical network with five different consumers (A, B, C, D and E), it was verified that if any consumer is disconnected, there would always be important variations in the MR load curve. By deduction, as more components are added to this microgrid, the sensitivity to variations in individual load curves decreases. 0Making predictions about energy sources and demand is a task as old as EPS itself [12] Thus, the prediction task in the PES in use is commonplace and has well-known and established models [13]. As the DG is used in the EPS, the characteristics of seasonality, trend and stationarity change drastically. Furthermore, in the context of the GS, the way to plan and manage this system is no longer applicable: the centralized EPS goes through annual to five-year planning, while the SG will have to perform short-term predictions. This work focuses on the study of prediction in the scope of EPS and the applicability of this prediction in its intelligent behavior. Since REIs are the next ongoing evolution of the electric power system, they must have a consistent framework for short-term prediction, meeting the operating characteristics of SGs. Classical prediction methods such as econometric and Box-Jenkins models [14] have been used over the years to predict the supply and demand of electricity for large interconnected systems. For short-term prediction problems, heuristic solutions are often proposed, such as those based on support vector machines SVMs.

1.4 THESIS OBJECTIVES

The objectives of this work are to analyze and develop methods for predicting energy demand and supply in an SG in the context of Smart Grids.

1.4.1 Specific Objectives

The specific objectives of this thesis are:

a. Present the systematics of prediction methods for long memory processes;
b. Present the relationship between prediction processes in microgrids and long memory processes;
c. Present the relevance methods and their derivatives in this context of forecasting energy supply and demand in the context of smart grids;
d. To develop innovative methods and algorithms for prediction in smart grids.

1.5 THESIS CONTRIBUTION

All the assumptions of an EPS are based on the autonomous behavior of its subsystems. Actions such as detection and isolation of faults, electronic negotiation of purchase and sale of electricity, determination of fraud and reconfiguration of distribution networks, among others, must be carried out autonomously, actively, so that the network can anticipate problems and thus display intelligent behavior. Based on robust prediction methods, the various agents present in the system may have learning and anticipation capabilities, thus implementing a completely autonomous and intelligent system. Several methods of prediction and machine learning are implemented in current electrical systems. All these methods are adapted to the reality of large interconnected systems and their classical energy sources. With the development of Smart Energy Grids (SEG), new methods adapted to this new reality are required. REIs have a large share of Distributed Energy Sources (DES) and an active negotiation between energy producers and consumers. Therefore, methods capable of making predictions in a short period of time based on time series that exhibit dependence on long memory are essential. This work intends to contribute in the research area of prediction methods for Long Memory Time Series. Classical methods in the area will be presented and discussed. With this, new proposals with a view to the efficiency and accuracy of the algorithms will be made.

2. LITERATURE REVIEW

2.1 INTRODUCTION

The conventional power grid is superior to the smart grid in a number of ways, such as having more advanced methods of measurement and sensing, information and communication technologies, simulation analysis, and control decision-making systems. [1-4] In comparison to traditional power distribution methods, the smart grid has a number of benefits, some of which are listed here. The conventional power grid is superior to the smart grid in a number of aspects, including the smart grid's ability to self-repair, consumption of renewable energy, situational awareness, information interaction, and grid stability [5,6]. Both the level of complexity and the degree of unpredictability that are involved in the operation of power systems have significantly increased as a result of the expansion of the electricity market and the availability of intermittent and distributed generation. This growth in the electricity market has been primarily responsible for these developments. As time goes on, it is becoming increasingly clear that the smart grid is undergoing a transition into a power cyber-physical system that intricately combines measurement, communication, and a variety of systems that are external to the grid (such as the market, the weather, etc.) [7,8]. The data that it produces are, as before, multi-source, high-dimensional, and heterogeneous in nature. In spite of the fact that the emergence of massive data presents a new challenge to the management of smart grids, this phenomenon also has the potential to provide data support for the investigation of smart grid issues. Recently, the problem of effectively and efficiently analyzing large data sets derived from a variety of sources in order to derive actionable insights for decision making regarding smart grids has recently come to the forefront [9]. The goal of this analysis is to derive actionable insights that can be used in decision making. Because it is necessary to bring this problem to light in order to derive actionable insights for decision making regarding smart grids, it has been brought to the forefront of our attention. Because this type of technology can improve both the rate at which decisions are made as well as the level of precision in those decisions, its implementation is essential to the achievement of the goals that have been established for the smart grid [10]. The field of machine learning (ML), which is a subset of artificial intelligence (AI) and represents the central technology and creative core of AI, can be credited for a significant portion of the progress that has been made in the area of artificial intelligence (AI) technology. ML is an acronym for "machine learning," which stands for "machine learning," which stands for "machine learning," which stands for "machine learning," which stands for "machine learning," The term "machine learning" (ML) is an acronym that stands for "machine learning," a subfield of artificial intelligence. ML is an abbreviation for the phrase "machine learning." (AI). The incorporation of machine learning into smart grids is one of the most exciting and potentially fruitful areas for technological advancement in the energy sector. It is also one of the most interesting areas. This is one of the most interesting parts of the country. Despite the fact that machine learning algorithms require a significant amount of processing power, they can only make a limited number of assumptions. The algorithms are given the ability to unearth the intricate connections that are concealed within the historical data thanks to this constraint. [11].

2.2 RELATED WORKS

2.2.1 Machine Learning and Power Systems

Because they can be used to create input-output relationship maps for the complex mechanisms that make up the smart grid, the application of ML algorithms is ideal for handling the problems that are associated with the smart grid. This is because ML algorithms are ideal for handling the problems that are associated with the smart grid. This is because the breadth of our current physical knowledge is not sufficient to adequately cover the intricacy of the workings of the smart grid. The reason for this is due to the fact that our present-day physical knowledge is limited. It is necessary to evolve and upgrade the underlying machine learning (ML) algorithms in order to develop energy systems that are more efficient, flexible, and long-lasting. These goals can be accomplished by making energy systems. A few examples of these algorithms include the linear regression (LR) algorithm [12], the support vector machine (SVM) algorithm [13], and the algorithms [1] and [2]. Digital communication systems, such as smart meters and smart appliances, as well as renewable energy sources and resources that are efficient with energy, all work together to make smart grids a reality. [Citation needed] [Citation needed] [Citation needed] [Citation needed] [Citation needed] [Cit The following are examples of these resources and resources that are efficient with energy: It is possible for power to flow in both directions, which contributes to an increase in the reliability, safety, and effectiveness of power systems [3, 4]. There is both a unidirectional and a bidirectional flow of information as a result of the fact that information generators and information users are able to communicate with one another in both directions. Intelligent grids are able to perform as a cohesive and effective entity because they make use of the most cutting-edge metering, control, and communication systems available. The strategic application of data has made this outcome conceivable. This specific application of artificial intelligence (AI) has gained a lot of traction in recent times and is having a significant impact on the world as it is known to people today. The progression of the electric grid will continue with the next step being the development of technology known as smart grids. Combining more conventional approaches with contemporary ones that are founded on artificial intelligence and machine learning is one way to achieve this goal. The next step in the evolution of the electric grid will be the implementation of cutting-edge technology that will be referred to as "smart grids." Recent developments in artificial intelligence and machine learning have the potential to make smart grids more resilient to disruptions and stable in the face of unanticipated circumstances. When it comes to load forecasting, determining the stability of the power grid, locating faults, and addressing security concerns in both the smart grid and power systems, it may be beneficial to make use of techniques from artificial intelligence. These responsibilities can each be carried out in a more efficient manner. According to Azad et al. [16], the smart grid's stability, reliability, security, efficiency, and responsiveness are all able to be improved with the assistance of various machine learning approaches In addition to this, we have discussed some of the challenges that may be encountered when putting machine learning-based smart grid solutions into practice. Some examples of these challenges are as follows: Zheng et al. [17] have developed ML models based on historical data in order to learn how the schedulable loads of customers and the predicted daily electricity price profile affect the profits of aggregators. These models were developed in order to learn how these factors interact with one another. The purpose of developing these models was to gain an understanding of the ways in which each of these factors interacts with the others. The machine learning classification and regression algorithms known as K-Nearest Neighbor (KNN) and Gaussian progress regression were selected as the best choices for the purpose of this investigation because of their consistent performance and accurate results. The purpose of this investigation was to investigate the relationship between the two variables. Bomfim [18] has investigated the process that was followed in the production of ML's smart grid applications through the use of primary and secondary sources. Through the utilization of a quantitative descriptive analysis of journal and newspaper articles that have been archived in the IEEE Xplore Library, he has provided a summary of work that has been done in the field of smart grids that has made use of machine learning. This work has been done in the context of the work that has been done in the field of smart grids. (ML). After conducting an investigation, he arrived at the conclusion that the aspects of smart grids that have received the most attention from researchers are the safety and reliability of the electrical network, as well as energy management and forecasting. He came to this conclusion after coming to the realization that smart grids are becoming increasingly popular. You and your colleagues [19] have demonstrated that AI has the potential to speed up model development and numerical computation of stability assessment in smart grids, compared to traditional simulation-based approaches. This is important because smart grids are becoming increasingly important in the energy industry. This is significant because the energy sector is moving toward placing a greater emphasis on the use of intelligent grids. This is significant because the energy industry is moving toward putting a greater emphasis on the utilization of intelligent grids, so this development is also moving in that direction. In addition to this, the presentation included a tool that is based on machine learning (ML) and is used to evaluate the transient stability, frequency stability, and small signals of power grids. This tool was included in the presentation.

2.2.2 Deep Learning and Smart Grids

This tool was a part of the presentation that we gave. They put their proposed model through a series of tests, and the results turned out to be very encouraging for the most part. Hossain et al. [6] have finished their exhaustive research into the application of big data and machine learning in smart grids, which are the next generation of electrical power systems. [Smart grids] are the next generation of electrical power systems. They claim that the Smart Grid system, which includes the Internet of Things, is able to provide accurate load forecasting as well as data acquisition at a price that is affordable for individual consumers. Methods that are many orders of magnitude more advanced than those that were previously utilized are required in order to properly analyze and make decisions based on the enormous amounts of data that are produced by smart grids. This is necessary in order to properly make use of the data. Methods such as artificial intelligence and machine learning are examples of these approaches. It is absolutely necessary to carry out activities such as feature extraction and analysis in order to improve the design of cutting-edge industrial systems such as smart grids. These kinds of systems require a high level of sophistication in their architecture. These alterations are an absolute requirement at this point. In this regard, Günel and Ekti [20] have detailed the advantages that can be gained as a result of employing ML strategies in one's work. They went over the machine learning algorithms and provided a concise summary of how those algorithms can be implemented in smart grid systems. Verma et al. [21] demonstrated that the utilization of forecasting methods such as artificial neural networks (ANNs), deep learning methods, and other techniques that are analogous to these have increased the possibilities for the planning and operation of smart grids. These possibilities were demonstrated through the utilization of artificial neural networks (ANNs), deep learning methods, and other techniques. [ANNs] In their paper, the authors provide a review of the previous research that has been conducted on various smart grid components. They have arranged the works into categories according to the computational intelligence tools that were utilized in each of the works that they surveyed in order to find a solution to a problem involving planning or operations. Recent advancements in the application of artificial intelligence (AI) methods for the stability analysis and control of smart grids have been outlined by Shi et al. [22] in a substantial amount of detail. These advancements have been made in recent years. In their presentation, which was a comprehensive overview of the field, they discussed the definitions of artificial intelligence, the historical context of the field, as well as cutting-edge research methodologies. In addition to this, they have presented a comprehensive analysis of the ways in which artificial intelligence can be utilized for the evaluation of the stability of smart grids, the diagnosis of faults, the control of stability, and the evaluation of the security of smart grids. The application of strategies driven by AI has produced results that are significantly more favorable than were anticipated, which has produced a strikingly positive outcome. They have also proposed solutions to these issues, which will help to close the gap between theory and application and will strengthen the utilization of artificial intelligence in the stability analysis and control of smart grids. These solutions have been proposed by the researchers. These are the potential solutions that the researchers have suggested. Because of the inherent complexities, inherent unpredictability, and massive amounts of data that are produced by smart grids, it is possible that the application of AI techniques will be required in the not too distant future. This would be done in order to ensure that the expansion and development of smart grids continues unabated, which is the primary goal of the proposed action. In a recent article, Zhang et al. provide a concise overview of the potential applications of deep learning (DL), reinforcement learning (RL), and the combination of the two, deep reinforcement learning (DRL), for use in smart grids. DRL stands for deep reinforcement learning. DL stands for deep learning. This overview is a part of the publication that was released. In addition to this, they have provided a summary of the studies that were recently conducted on their potential applications in the emerging field of smart grid technology. These studies were carried out relatively recently. The meteoric rise of AI 2.0 can be attributed to a confluence of factors, the most prominent of which are the pervasiveness of data, the falling cost of computing power, and the easy availability of more advanced AI algorithms. The meteoric rise of AI 2.0 can be attributed to a confluence of factors, the most prominent of which are the pervasiveness of data. The meteoric rise of AI 2.0 can be attributed to a confluence of factors, the most prominent of which is the pervasiveness of data. However, the rise of AI 2.0 has been attributed to a confluence of factors. Artificial intelligence (AI) and other technologies that are currently available have the potential to improve the functionality of smart grids, which are the most prominent trend in the evolution of power systems at the moment. This improvement could be accomplished through the use of technologies that are currently available. The utilization of AI in conjunction with various other technological advancements might make it possible to achieve this improvement. It is anticipated that the implementation of smart grids will result in significant improvements to power generation, transmission, and consumption when compared to traditional electrical systems. These enhancements will be brought about by comparison. The concept of demand response, which is also referred to as DR, is an essential component of the smart grid. This is so because it encourages customers to take part in activities that aim to reduce the total amount of energy that is consumed. It is absolutely essential to have an accurate forecast of future electricity consumption if one wishes for the market to continue to be in a state of healthy equilibrium between the supply of electricity and the demand for it. The assistance provided by predictive models that are built on machine learning makes it now possible to have foresights that are comparable to the one presented here.

2.2.3 AI and Smart Metering

The smart meters that are an essential part of the infrastructure for a smart grid are in charge of sending information about individual users to a centralized server. This information can then be analyzed and acted upon. With the help of ML techniques, it is possible to develop predictive models for the processing of data from smart meters. This can be accomplished by using the data from smart meters. The most cutting-edge artificial intelligence (AI) methods that can be used to support instantaneous and timely demand response were outlined in recent research that was carried out by Ali and Choi [24]. This research was carried out by Ali and Choi. These techniques can be implemented to assist in the support of instantaneous and timely demand response. Recent advancements in artificial intelligence have made it possible to implement expert systems in the energy sector that make use of artificial neural networks (ANN) and fuzzy logic. These systems are able to do this because of recent advancements in AI. These systems are now practicable as a direct result of recent developments in technological capability. These systems were developed specifically for residential energy management, particularly within the context of smart homes that make use of DR programs. In addition, they were developed for overall demand-side management and for the management of residential energy demand in a more general sense. (DSM). It is an essential component of the smart grid to implement DR because it has the potential to cut costs while simultaneously increasing reliability. The investigation of DR has garnered an ever-increasing amount of interest over the course of the past few years, and this trend looks to continue. The concept of disaster recovery is distinguished by a number of distinguishing characteristics, the most notable of which are its extensive data mining, instantaneous judgment, and extreme complexity. The process of making demand side response more accessible is significantly aided by both artificial intelligence and machine learning, which play an important role in the process. Antonopoulos et al. [25] have provided comprehensive coverage of the various approaches to artificial intelligence (AI) techniques, ensuring that your needs are met in every conceivable way. After conducting research on more than 160 papers, 40 businesses, and 21 significant projects, they arrived at the conclusions that they had reached. They have demonstrated, through the work that they have done, that there is a growing demand for AI-based disaster recovery solutions. [Citation needed] [Citation needed] These advancements have made it possible to use tools for prediction, real-time efficient control of distributed systems, and decision-making. All of these capabilities can now be applied to disaster recovery as a result of the advancements made in artificial intelligence. Since accurate load estimation and prediction are required for the efficient operation of the power grid, load forecasting in DR has incorporated AI and ML techniques in order to improve accuracy. This is because accurate estimation and prediction of load are necessary for the effective operation of the power grid. This was done because the successful operation of the power grid depends on the utilization of these methods to their full potential. Predictions have also been made regarding the prices of future electricity, but this time with the assistance of methods derived from artificial intelligence. Grid operators who incorporate AI into the process of disaster recovery are able to increase their chances of ensuring that everything continues to operate normally after an incident. After the installation of smart meters, a substantial amount of data is collected from customers regarding the total amount of power that they consume. In order to build trustworthy smart grids that are also effective in their utilization of energy, the application of probabilistic load forecasting is an absolute necessity. (PLF). Bayesian deep learning is the approach that Yang et al. [26] have taken in order to find a solution to this difficult problem that they have identified. Bayesian deep learning is an approach that uses the Bayesian network. They have proposed the development of a novel multitask PLF framework that is based on Bayesian deep learning in order to quantify the uncertainties that are shared across distinct customer groups while also taking into account the differences that exist between those groups. This would allow them to quantify the uncertainties that are shared across distinct customer groups. Because of this, they would be able to take into account the differences that do exist between the various groups of customers.

2.2.4 Clustering of Power Data

They devised a clustering-based pooling strategy in order to increase data diversity and volume, which ultimately assisted them in preventing overfitting and improving the predictive capabilities of the model. The amount of information that could be gathered was the primary focus of this tactic. The findings of the evaluations that were carried out showed that the performance of the proposed model was noticeably more successful than that of the conventional methods. These findings were shown by the fact that the proposed model outperformed the conventional methods. Incorporating load forecasting technology into the infrastructure of future smart grids will be of tremendous assistance to the development of such grids. It is very common for traditional statistical and ML methods to result in errors in predictive modeling, in addition to severe overfitting. The reason for this is that conventional statistical and ML methods are predicated on certain assumptions about the data. An energy load forecasting (ELF) model for smart grid energy management is proposed by Mohammad and Kim in the article that they wrote (27), and it is based on the architecture of a deep neural network. This model was developed for smart grid energy management. This model is meant to assist in lowering overall energy expenditures. Deep feed-forward neural networks (deep-FNN) and deep recurrent neural networks (deep-RNN) have both been the focus of research that has been carried out to investigate the capabilities and potential of both of these types of networks. (Deep-RNN). In order to compare the two architectures' respective levels of performance, simulations of both were run using a training set of varying sizes. We have also compared the mean absolute percentage error of the simulation results for the various architectures that make use of a wide variety of activation functions and various combinations of hidden layers. This was done in order to determine which architecture produces the most accurate results. In order to determine which architecture yields the most accurate results, this was carried out. They came to this conclusion after comparing their findings to those obtained from a variety of load forecasting models and discovering that the model they proposed performed noticeably better than those obtained from the other models. As a result of this discovery, they came to the conclusion that this was the most accurate way to predict future load levels. Kuo and Huang [28] have developed an algorithm that is based on a deep neural network and accomplishes both of these goals. The algorithm is used to make accurate and timely projections of short-term load, and it achieves both of these goals simultaneously. (STLF). In order to draw conclusions about the proposed load forecasting model's overall effectiveness, its performance was evaluated and compared to that of five other well-known artificial intelligence algorithms. This was done in order to determine whether or not the model was effective. The algorithms under consideration were the Random Forest (RF), the Support Vector Machine (SVM), the Decision Tree (DT), the Multi-layer Perceptron (MLP), and the Long Short-Term Memory network. (LSTM). They have been able to achieve a very high level of accuracy in their forecasts by achieving a model Mean Absolute Percentage Error (MAPE) of 9.77% and a Cumulative Variation of Root Mean Square Error (CVRMSE) of 11.66%. This allows them to achieve a very high level of precision. Both of these numbers refer to the degree to which their models are accurate. In order to avoid the severe repercussions that are brought on by price dynamics, it is essential for smart grids to have trustworthy and accurate price forecasting. These results are a direct result of the price fluctuations that have occurred. Atef and Eltawil [29] have come up with not one but two ingenious strategies for making use of ML in order to solve the problem of electricity price forecasting. Both of these strategies make use of the fact that ML is able to predict future prices. In order to accomplish their objectives, both strategies make use of machine learning. (EPF). They began by applying a model known as Support Vector Regression (SVR), which makes hourly price predictions, and compared its performance to that of a model that makes use of deep learning. When compared to the SVR model, the deep learning method's average root mean square error was 1.1165, while the SVR model's error was only 0.416. This discrepancy suggests that the deep learning method is more accurate. This finding demonstrates that the SVR model is inferior to the deep learning method, which demonstrates that deep learning is superior. Lu et al. [30] propose using a decision system that is founded on reinforcement learning as a means of facilitating the process of selecting appropriate pricing plans for one's home's electric service. The use of this system has been suggested as a method for facilitating the decision-making process. This is done with the intention of lowering the overall level of dissatisfaction that each final user of a smart grid has regarding the payment for and consumption of electrical power. The goal of this action is to make the final user of a smart grid more satisfied. They modeled the decision problem as a transition probability-free Markov decision process (MDP) with an enhanced state framework, and then they solved it with a Kernel approximator-integrated batch Q-learning algorithm. The MDP was enhanced with a state framework. The MDP was improved by the incorporation of a state framework. They were able to enhance the accuracy of both the computations and the predictions as a result of this. The algorithm that they proposed is one that is capable of searching a continuous, high-dimensional state space for the underlying characteristics of dynamic pricing structures over the course of time. The preliminary findings of the testing have revealed some extremely promising signs, which provides cause for optimism. As a result of this, it is now possible to formulate predictive policies that are not only extremely accurate but also user-specific and predictive in nature.

3. MATERIALS AND METHODS

3.1 INTRODUCTION

Since the beginning of the 20th century, the study of the stability of the electrical network has been recognized as an important issue, and it has been the subject of serious concerns on the part of researchers [20]. This concern stems from the fact that the stability of the network is a subject that has been the subject of serious concerns since the beginning of the 20th century. Throughout the course of network history, the predominant stability issue that has been tackled on the overwhelming majority of networks is known as transient stability [21]. In spite of this, the increased operation of networks at their boundary conditions has resulted in the emergence of a number of other forms of stability, such as voltage stability, frequency stability, and so on. It is essential to have a crystal clear understanding of the various types of stability as well as how these types of stability are related to one another in order to successfully design appropriate tools for the prediction of instability in real time. Only then can a successful design of appropriate tools for the prediction of instability in real time be achieved. To illustrate this point, throughout the entirety of this thesis. In this chapter, we propose to define stability on a global scale as well as within the context of the specific architecture of electrical networks, all while identifying the various types of stability that are typically found on those networks. Additionally, we will identify the various types of stability that are typically found on those networks. After that, we will discuss the theoretical underpinnings of stability as well as the mathematical model that was utilized in order to evaluate it. Following that, we will discuss the mathematical model. In conclusion, we look at the differences and similarities between the various modes of operation that electrical networks can make use of. 3.2 Definition and classification of stability on electrical networks

3.2 DEFINITION AND CLASSIFICATION OF STABILITY ON ELECTRICAL NETWORKS

On electrical networks, a collection of means are put into place in order to keep the frequency and voltage quantities as close as possible to their respective setpoint values. A condition in which opposing forces are balanced is referred to as stability. It is possible for there to be a certain imbalance, which may or may not persist over time, between the various opposing forces that lead to forms of instability. This imbalance can be caused by the topology of the network, its state of operation, and the types of disturbances that are present. Developing methods for analyzing stability and determining the primary factors that contribute to instability both inevitably require a good categorization of the type and nature of stability. Identifying the key factors that contribute to instability and determining how to analyze stability with this in mind, we will relate, in the following section, the many different phenomena of stability by classifying them.

3.2.1 Classification of The Stability of Electrical Networks

The problem of correctly classifying the stability of electrical networks is one that has been around for a very long time. The first steps toward classifying stability phenomena were taken in these publications [22], which laid the groundwork. However, the definitions do not accurately reflect the needs of the industries at the present time, nor do they take into account the various scenarios of instability that are very common on the networks of today. Figure 3.1 [23] presents a classification that has been adapted to work within the parameters of contemporary electricity networks. In particular, it takes into account the amount of time necessary to determine the network's stability, as well as its physical nature and the various types of contingencies that can affect it. The idea of partial stability provides a theoretical basis for supporting its justification. [24]

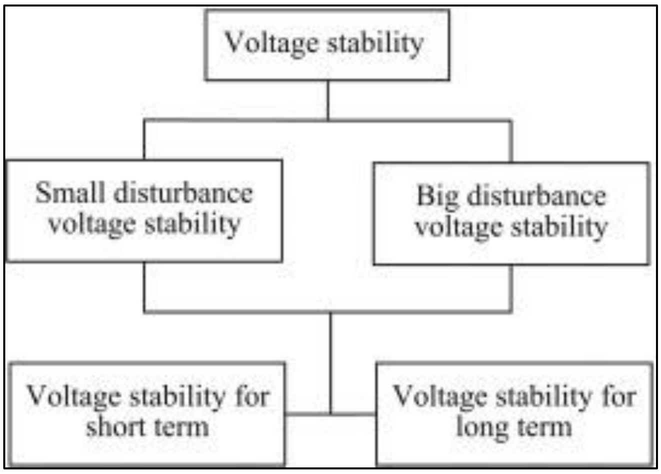

Figure 3.1: Classification of Stability Phenomena in Electrical Networks [24].

The ability of synchronous machines to keep their synchronism after a disturbance is referred to as "rotor angle stability." This ability is also known as the capacity to maintain or restore the equilibrium between the electromagnetic torque and the mechanical torque produced by each machine in the network. This is accomplished by maintaining the rotor angle at a constant value. An increase in the angular difference between two or more machines is one of the telltale signs that instability has set in. This trend persists until synchronism between all of the machines has been eliminated entirely, and it does so until the angular difference between the machines continues to grow. The problem of maintaining rotor stability has prompted researchers to look into electromechanical oscillations as a possible solution. The relationship between the powers of synchronous machines is typically analyzed as a function of the angle at which the rotor is spinning because this is the most common scenario. During the steady state, the speed remains constant, and there is a balance between the mechanical torque and the electromagnetic torque that is produced by each machine. If the network is struck by a contingency, the equilibrium will be disrupted, which will cause the machines to either speed up or slowdown in accordance with the laws of motion that govern the motion of a rotating body. These laws govern the motion of a rotating body in accordance with the laws of motion that govern the motion of a rotating body. If one generator operates at a higher speed than the others, the angular position of the rotor of the faster-running generator will be higher in comparison to the position of the generator that operates at a slower speed. Because of this significant angular difference, a portion of the load that was being carried by the machine that was moving more slowly is transferred to the machine that was moving more quickly. This has the effect of slowing down both machines and reducing the angular deviation. An increase in the angular deviation is accompanied by a decrease in the transfer of energy once a certain limit has been exceeded; as a result, the angular position continues to increase beyond that point. If the network is unable to absorb the kinetic energy that is caused by these variations in rotor speed, then the system will be unstable. This is because the variations in rotor speed cause the system to behave in an unpredictable manner. [25]

Rotor stability is broken down further into its component sub-categories, which are small signal stability and transient stability. The first one has to do with the capability of the network to keep its synchronization even when confronted with relatively minor disturbances, which enables it to linearize the systems of equations that describe the current state of the network [26]. The second one has to do with the ability of the network to keep its synchronization even when confronted with relatively major disturbances. A lack of damping of oscillations is the primary cause of this type of instability on modern electrical networks [27], which are fitted with a large number of voltage regulators. These networks also have a number of other safety features. If this damping issue only affects a single generator or a relatively small section of the network, then we refer to the issue as being local. (Local plant mode oscillations). On the other hand, a problem is regarded as being of a global scale if it can be seen to exist in the interactions between numerous large groups of generators. (interarea mode oscillations). The second issue is the degree to which the network is able to recover from significant disruptions, such as a short circuit that happens on a transmission line, while still maintaining its synchronization. The fact that there is a non-linear relationship between the power output of the generator and the angular position of the rotor [28] is the primary factor that contributes to the instability that occurs as a result of the generator. It is possible to notice it immediately after the fault (on the first swing), or it may take place over a longer period of time. Either way, it is possible to observe it. (Multi swing). The transient stability of the network is determined by a number of factors, including the initial operating conditions of the network, the location of the fault, the severity of the fault, the length of time it lasts, the performance of the protection systems, and the dynamic characteristics of the various pieces of equipment. Both of these types of instability are regarded as being short-term occurrences, with an investigation lasting somewhere between ten and twenty seconds at most. According to the findings of the studies that have been conducted, the idea of dynamic stability can also be referred to as rotor angle stability. On the other hand, there are authors who make use of it to talk about a wide variety of distinct occurrences. When referring to Europe, this term refers to a stability that is only temporary [29]. This is a term that refers to the stability of small signals that can be achieved over a network through the implementation of automatic controls [30]. A definition that is utilized in other parts of the scope of this thesis, and one that we choose to adopt as our own. The primary factor that determines voltage stability is the capacity of the network to maintain stable voltages at the busbars after being subjected to a disturbance for a given set of initial operating conditions. This capacity is what is known as the voltage stability margin. It is necessary to either maintain or reestablish the balance that currently exists between the load and the generation of electricity. This instability is observed to take place when a particular voltage threshold is exceeded, which leads to a gradual drop in voltage because of the load. This drop in voltage causes the instability to take place. [31]This phenomenon is sometimes referred to as a voltage collapse by those who are familiar with it. When there is an emergency, this kind of instability is almost always caused by a demand for reactive power that is greater than the amount that is available on the network [32]. This kind of instability can also be caused by a number of other factors. Unstable voltage has a number of potential outcomes that could occur, including the loss of load in an area, the tripping of production lines, and the malfunctioning of devices in the protection system. The consistency of the voltage can be divided into two different categories: large disturbances and small disturbances. Small disturbances are a reflection of the network's ability to maintain stable voltages in response to relatively minor changes, such as those brought about by incremental shifts in load. These types of changes can occur as a result of incremental shifts in load. This type of instability can be caused by a number of factors, including the characteristics of the loads, the controls (both continuous and discrete), and a variety of other factors. In such a scenario, the equations that describe the network can be linearized so that its stability can be assessed. [33] Large disturbances are the capacity of the network to maintain constant voltages following the occurrence of significant faults, such as the loss of generation. Large disturbances can occur when the network is unable to maintain constant voltages. This capacity is determined not only by the characteristics of the loads but also by the interactions between the discrete and continuous controls as well as the protection systems. In order to have a proper understanding of events of this nature, it is necessary to conduct an analysis of the nonlinear response of the network [34]. In either case, the amount of time necessary to investigate the stability phenomenon can range anywhere from a few seconds to ten minutes, depending on how in-depth the investigation needs to be. The reason for this can be understood by considering the fact that Figure 3.1 addresses both short-term and long-term occurrences of the phenomenon being discussed. This capacity is determined not only by the characteristics of the loads but also by the interactions between the discrete and continuous controls as well as the protection systems. In order to have a proper understanding of events of this nature, it is necessary to conduct an analysis of the nonlinear response of the network [35].In either case, the amount of time necessary to investigate the stability phenomenon can range anywhere from a few seconds to ten minutes, depending on how in-depth the investigation needs to be. The reason for this can be understood by considering the fact that Figure 3.1 addresses both short-term and long-term occurrences of the phenomenon being discussed. This capacity is determined not only by the characteristics of the loads but also by the interactions between the discrete and continuous controls as well as the protection systems. In either case, the amount of time required to investigate the stability phenomenon can range anywhere from a few seconds to ten minutes at the absolute most. It is necessary to carry out an investigation into the nonlinear response of the network in order to gain an understanding of events of this nature. The reason for this can be understood by considering the fact that Figure 3.1 addresses both short-term and long-term occurrences of the phenomenon being discussed. What is meant by the term "frequency stability" is the capacity of the network to keep the equilibrium frequency on the network or to restore it after a severe disruption that is brought on by an imbalance between generation and load. This is what is meant by the term "frequency stability." The instability that is brought about as a consequence appears in the form of sustained frequency fluctuations. In order to correct this imbalance, it is possible to make use of the kinetic energy that is stored in the rotating parts of synchronous machines [37]. As a consequence of this, the generators that are taking part in the frequency control will adjust the total amount of active power that is supplied in order to bring the frequency back to values that are considered to be acceptable. [38] But, if the frequency difference is too large, we can witness a complete collapse of the network. Generally, frequency stability problems are associated with inadequate plant power responses, poor coordination of control and protection systems or lack of production [39]. In islanded networks, there is also such instability in the event of a significant loss of load or production [40] During this instability, variations are observed in the amplitude of the voltages. These phenomena can last from a fraction of a second (short term) to minutes (long term). It is important to distinguish the different forms of stability to fully understand the underlying causes in order to design appropriate and adequate tools for the effective and efficient operation of power networks. Even if we are interested in a specific case of stability, we must always keep in mind that the final objective is to maintain stability globally throughout the network.

3.2.2 Relationship Between Reliability, Security and Stability of Electrical Networks

The purpose of this subsection is to clarify the distinctions between the reliability, security, and stability of electrical networks. This is necessary due to the frequency with which these terms are applied in a manner that is inaccurate, and the purpose of this subsection is to clarify these distinctions. These clarifications will help avoid confusion in other areas as well, including with regard to the reliability and security metrics that were adopted in Chapter 5 to evaluate the performance of the prediction model. This is because these clarifications will help avoid confusion in other areas. What is meant by the term "reliability" when referring to an electrical system is the ability of that system to provide adequate electrical service continuously despite the possibility of interruptions occurring over time [41]. The probability that an electrical system will continue to function satisfactorily over a considerable amount of time is central to the concept of reliability. The level of security of an electrical network is directly proportional to the network's ability to withstand impending disturbances without suffering an interruption in service. It is comparable to the consistency that the network possesses [42]. On the other hand, stability refers to the process of ensuring that the network's production and consumption remain in a state of equilibrium. Remembering this is essential because it was covered earlier in the conversation. When it comes to the design and maintenance of an electrical network, achieving maximum levels of dependability should always be the top priority. In order for something to be reliable, its safety needs to be ensured on an almost continuous basis. Stability is an aspect of this security, but it also includes protection against other dangers that are not considered to be issues with stability. Examples of risks that do not fall under the category of stability issues include, for instance, damage to equipment such as the failure of transmission and distribution cables, the falling of towers caused by the accumulation of ice [43], etc. On the other hand, despite the fact that a system might be stable after an unexpected event has taken place, this does not necessarily imply that it operates in a risk-free environment. Two potential causes of this issue are an overloading of the equipment, which may or may not have occurred, and voltage violations in the post-fault configuration. I' Stability analysis is therefore an essential component of both the security study and the evaluation of the dependability of the network. This particular thesis will only focus on the problem of consistency in its discussion.

3.3 THEORETICAL FOUNDATIONS OF ELECTRICAL NETWORK STABILITY

In this section, we address the fundamental questions related to the definition of the stability of the electrical network from the theoretical point of view. The classic study of the stability of an electrical network consists of:

a. State modeling hypotheses and formulate an appropriate mathematical model for the study of phenomena over time.
b. Select a suitable definition of stability.
c. Simulate then analyze the stability for a set of contingencies.

d. Evaluate the results based on the assumptions, then compare them with reality.

3.3.1 Mathematical Definition of The Stability of A Dynamical System

The power grid model is assumed to be defined by a state model described by a set of condensed first-order differential equations.

In Figure 3.2, we describe in a two-dimensional vector space the behavior of trajectories in the vicinity of a stable equilibrium point. By choosing the initial conditions in a sufficiently small neighborhood of a sphere of radius, one can force the trajectory of the system at all times≥to be located entirely within a given cylinder of radius.

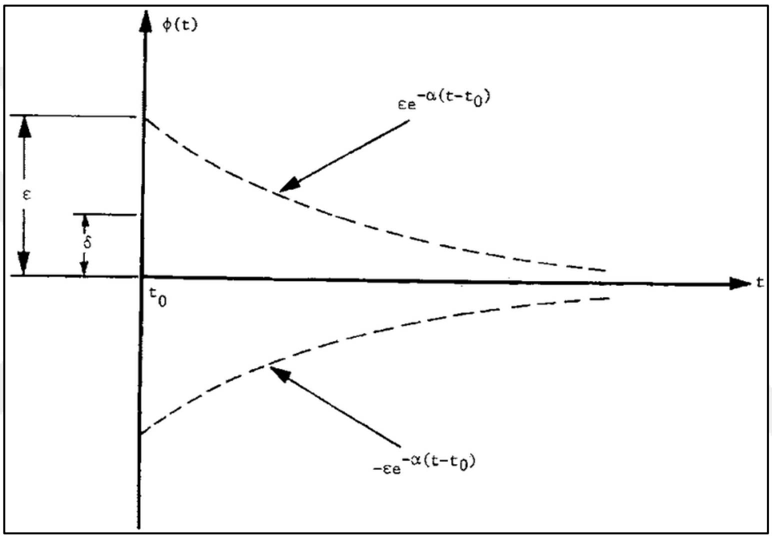

Figure 3.2: Illustration of the Definition of Stability [41].

Stability means that the trajectories do not change too much under small disturbances. The reverse situation, where a nearby (asymptotic) orbit is repelled from the given orbit, is also interesting. As shown in Figure 3.3, in general, perturbing the initial state in some directions results in the trajectory asymptotically approaching the given one and in other directions to the trajectory moving away from it.

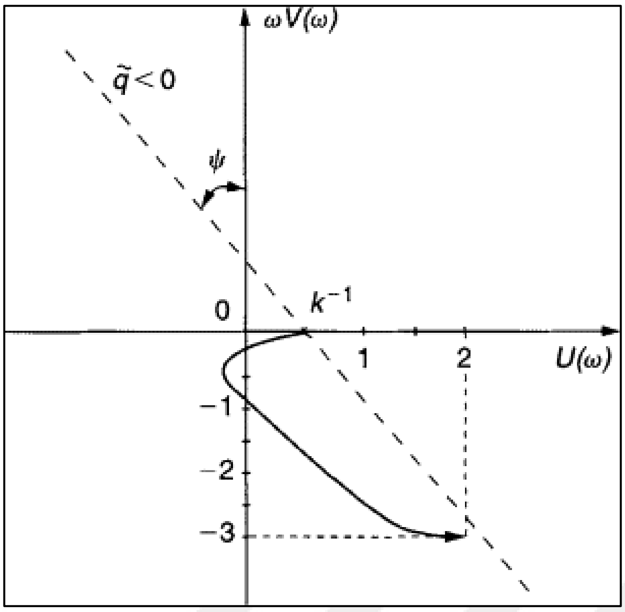

Figure 3.3: Illustration of the Definition of Asymptotic Stability [43].

3.3.2 Stability of Electrical Networks

By subjecting an electrical network to a fault, three distinct phases can be distinguished [44] A first phase which relates to the moment preceding the appearance of the fault (prefault); at this instant, the network is considered to be at rest. The second phase is when the fault occurs (fault-on). There will be a fault clearing time (clearing time, CT). The third phase is the post-fault phase during which the behavior and dynamics of the network are studied. A distinction is also made between a preemption time generally not exceeding 10 cycles to remedy the contingency and a critical time (critical clearing time, CCT) beyond which the network becomes irrevocably unstable.

3.4 MATHEMATICAL MODEL RELATED TO THE STUDY OF TRANSIENT STABILITY

Let Figure 3.4 be the simplified model of a synchronous machine represented by a sinusoidal voltage source in series with a resistance and a reactance through which a current flows and connected to a voltage bar [45]. For a network with several synchronous machines, each of them has exactly the same configuration seen in Figure 3.4 [46]

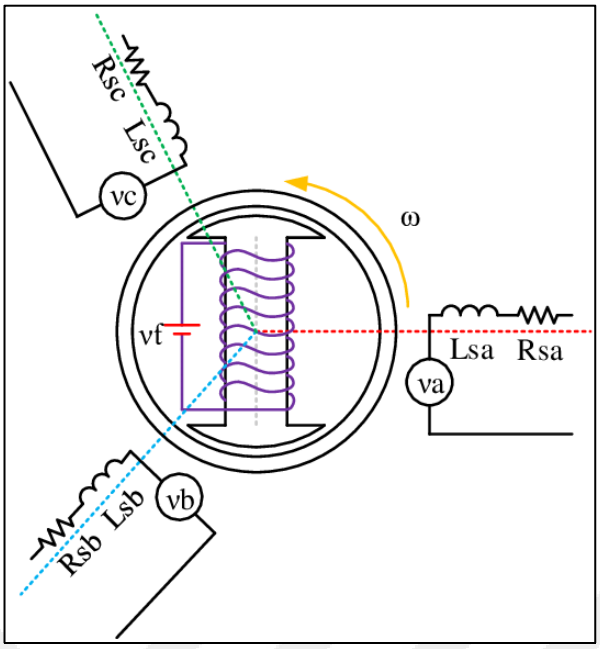

Figure 3.4: Simplified Model of a Synchronous Machine [46].

3.5 MODES OF OPERATION OF ELECTRICAL NETWORKS

The evaluation of electrical networks' transient stability is of the utmost significance in terms of the design, management, and planning of those networks. ([46]). The goal is to determine whether or not, in the event of a disruption on the network, the machines will reach the synchronous frequency for a stable equilibrium point of new power angles, new voltages at the busbars, and with a new power distribution without losing their ability to synchronize with one another. [47] The identification of the mode of operation of the network, which may include the state of prevention, the state of alert, and the curative mode, is a necessary step in the process of performing an accurate evaluation of the transient stability. This step may also be referred to as the state of prevention, the state of alert, or the curative mode. [48]. When deciding which method of transient stability analysis to use, the mode of operation should be given a great deal of consideration. The state of the network that is characterized by normally functioning nodes is referred to as the prevention state of the network. When the business is run in a preventive mode, it is able to completely fulfill the requirements of its clients or users. The goal of the control is to continue satisfying the demand without interrupting services at a lower cost, which is also the purpose of the control that is currently being carried out or will be carried out in preventive mode. Due to the fact that this mode of operation is relatively routine, network operators have a great deal of experience with it and are proficient in its use. Under these specific conditions, the occurrence of a contingency that might result in instability is an extremely remote possibility. The operators are aware of how to manage the balance in the event that there are minor issues. The operator will switch to the emergency mode of operation when the protective equipment has been seriously stressed or damaged. Either the voltage cannot be maintained at a value that is reasonable any longer, or the frequency of the signal will decrease. Both of these outcomes are possible. To put it succinctly, we are currently in a state in which there is a disruption in the synchronism. In a situation such as this one, the objective of the control actions should be to compensate for this loss by ensuring that the request is complied with to the greatest extent that is practically attainable. The significance of economic considerations is only marginal. In terms of the state of repair or the curative mode, we have arrived at a situation in which there is no way back; specifically, certain customers are no longer being served. This means that there is no longer an option for us to return to the previous state. The objective here is to move from a state of partial operation to one of complete satisfaction with the request. This will be accomplished by reducing the amount of time it takes to respond to a request. It is important to cut down as much as possible on the amount of time spent on maintenance. Either the voltage cannot be maintained at a value that is reasonable any longer, or the frequency of the signal will decrease. Both of these outcomes are possible. To put it succinctly, we are currently in a state in which there is a disruption in the synchronism. In a situation such as this one, the objective of the control actions should be to compensate for this loss by ensuring that the request is complied with to the greatest extent that is practically attainable. The significance of economic considerations is only marginal. In terms of the state of repair or the curative mode, we have arrived at a situation in which there is no way back; specifically, certain customers are no longer being served. This means that there is no longer an option for us to return to the previous state. 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This will be accomplished by reducing the amount of time it takes to respond to a request. The amount of downtime should be cut down to the smallest amount that is practicable.

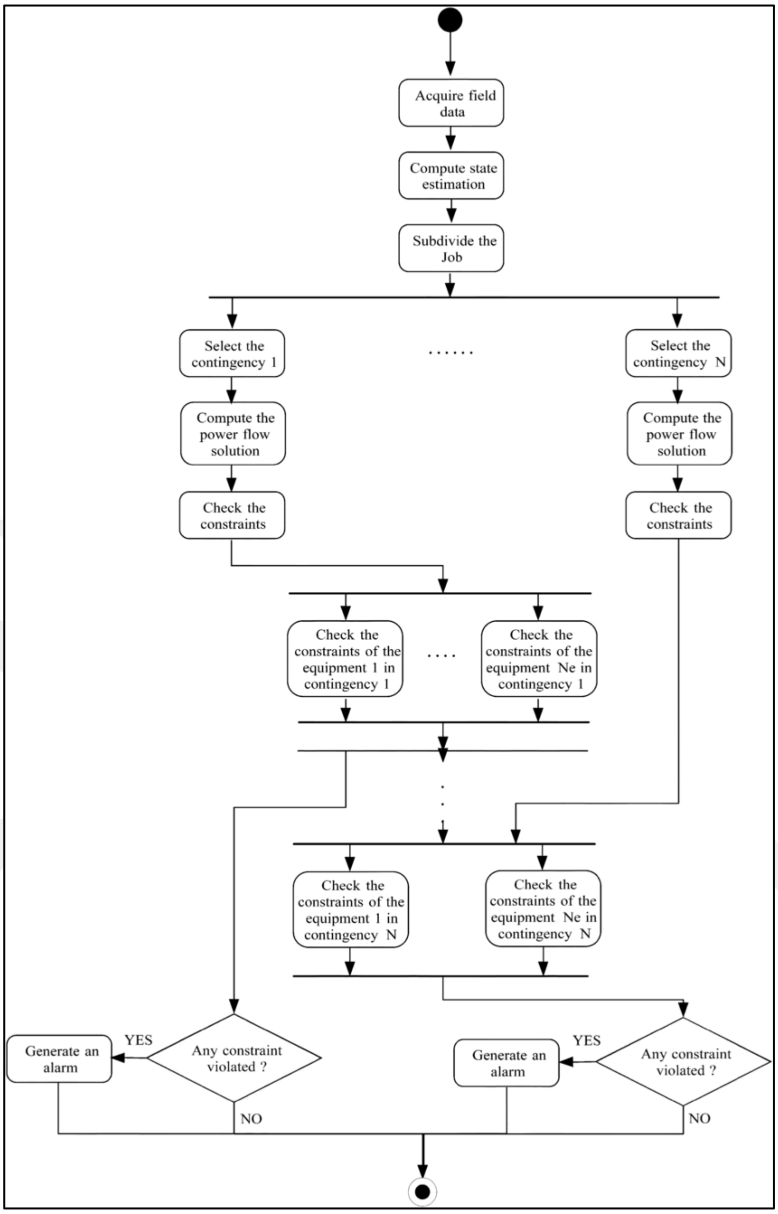

Figure 3.5: Power Grid Security Status Diagram [48].

Figure 3.5 is where you'll find a depiction of the safety state diagram that pertains to the various operational states of the electrical network. You can find it there. The arrows that are solid indicate a change in the mode of operation of the network as a result of a control action that was planned, whereas the arrows that are dotted indicate a change in the mode of operation of the network as a result of a control action that was either unexpected or performed incorrectly. The objective here is to ensure that the network is functioning in a preventative mode as much as is practically possible. Even though the preventive mode is currently engaged, it is still possible to conduct a network exploration as indicated by the arrows. We are able to conduct a study of the many different outcomes that are reasonably foreseeable, and we can populate a database with the relevant data that we obtain from this investigation. The objective of one strategy is to achieve the greatest possible financial gain, while the objective of the other is to mitigate the negative effects of happenings that cannot be predicted in advance. As soon as the alarm is triggered, our number one concern will be to reset the network so that it is operating in the preventive mode. We will not give up until we have found a solution that combines the preventative strategy with the potential control actions in a way that is both effective and efficient. Because the network contains a number of complexities, we are no longer in the alert state but rather in the curative mode at this time. This is a change from the previous state in which we were operating, which was the alert state. At this point, our primary objective and responsibility is to ensure that the network is returned to the state in which it can function normally.

a. Monitoring of electrical networks

i. First applications of PMUs

Only post-fault analyses were able to be carried out because there were so few PMUs from the first generation that were actually installed on the network. These PMUs were available on the market. The first measurements were carried out and recorded by PMUs in a WAMS in the year 1992 as a part of the Parameter Identification Data Acquisition System (PIDAS) project that was initiated by the Electric Power Research Institute. (EPRI). As part of the tests that were being run in the Scherer station in Georgia, the 500 kV lines from Klondike and Bonaire were opened and closed both manually and automatically at various points. In addition to this station, a manually activated PMU was shipped to four other stations located in the states of Georgia, Florida, and Tennessee. [47] After making a comparison between the positive results from the experiment and the values that were estimated using the data from the PMUs, the system model was able to be validated. Following the conclusion of these tests, a more comprehensive rollout was executed on the network in the United States. These served the function of a digital recorder to keep track of any disturbances that took place. Additional safeguards and regulatory mechanisms were incorporated as time progressed and new safeguards were added. When significant power outages occurred on the west coast of the United States in 1996 and on the northeastern coast of the United States in 2003, the data from PMUs were of great assistance in conducting post-mortem investigations of the causes of the power outages in a timely and accurate manner.

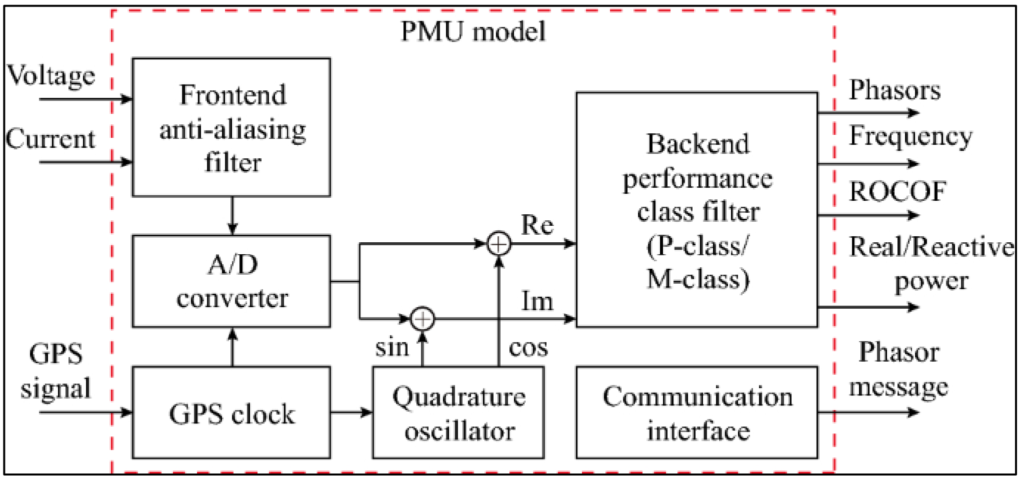

Figure 3.6: First applications of PMUs [47].

ii. State estimate

The term "state estimation" refers to one of the application functions that is utilized most frequently in control and management centers for electrical networks. (Energy Management System, EMS). Several different state estimator algorithms [48] use the power flows (both active and reactive power) and line power injections that are provided by the Supervisory Control and Data Acquisition system to estimate all angles as well as the network busbar voltage amplitudes. (SCADA). Prior to acquiring the PMUs, we were only able to access unsynchronized measurements, which did not always accurately reflect the actual state of the network. Having access to the PMUs has significantly improved this situation. The estimation of the state is, in a more general sense, a nonlinear iterative problem that can be solved by employing the method of weighted least squares. [49]. The introduction of synchrophase measurement technology has the potential to convert the iterative nonlinear state estimation problem into a straightforward linear one [50]. This could be accomplished by taking into account measurements from PMUs as well as data from SCADA. As a direct consequence of this, the precision of the measurements as well as the effectiveness with which the state estimators carry out their work has significantly increased as a direct result of the PMUs. In spite of this, the research that has been carried out so far still brings up the issue of whether or not the data obtained from PMU can be trusted or relied upon. [51]

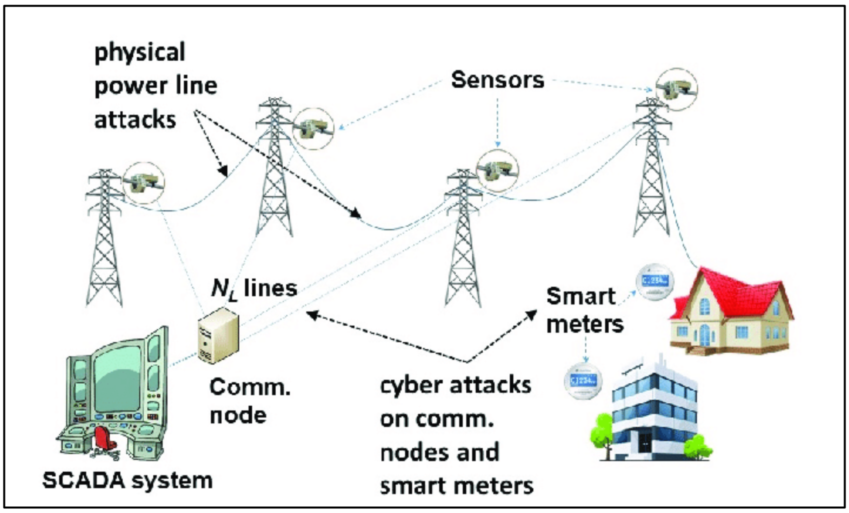

Figure 3.7: SCADA and Smart Grids [51].

As a direct consequence of this, the precision of the measurements as well as the effectiveness with which the state estimators carry out their work has significantly increased as a direct result of the PMUs. Despite this, the research [52] still brings up the issue of whether or not the data from PMU can be trusted or relied upon.As a direct consequence of this, the precision of the measurements as well as the effectiveness with which the state estimators carry out their work has significantly increased as a direct result of the PMUs. In spite of this, the research that has been carried out so far still brings up the issue of whether or not the data obtained from PMU can be trusted or relied upon. [53]

iii. Evaluation and validation

The implementation of PMUs gives the possibility to identify errors in network modeling parameters and to calculate improved estimates [54]. The data from the PMUs being reputed to be more precise, they can be used to determine, for example, the matrices of admittance, impedances and the exact tap data of the transformers. Moreover, in Europe, such an application is marketed to calculate the impedance of transmission lines [55].

b. Control of electrical networks

The control of the networks was carried out on a local level before the PMUs were introduced. For example, generators were only controlled by signals from the immediate area. By integrating all of the data from the WAMS, which is made possible thanks to PMUs, operational decisions can be made instantly and across the globe. We will have an easier time addressing issues pertaining to transient stability [53], electromechanical oscillations

[54], and specific overload phenomena. For example, from the measurements, a High-Voltage Direct Current (HVDC) controller can be called upon to dampen the electromechanical oscillations between two very distant regions of the network [55] or even stabilizers (Power System Stabilizers, PSS) can improve the stability of the network when it is coupled to an Automatic Voltage Regulator, AVR [56] In addition, logic controllers [57] that are the product of off-line data learning [58] can be incorporated into the network protection system [59].

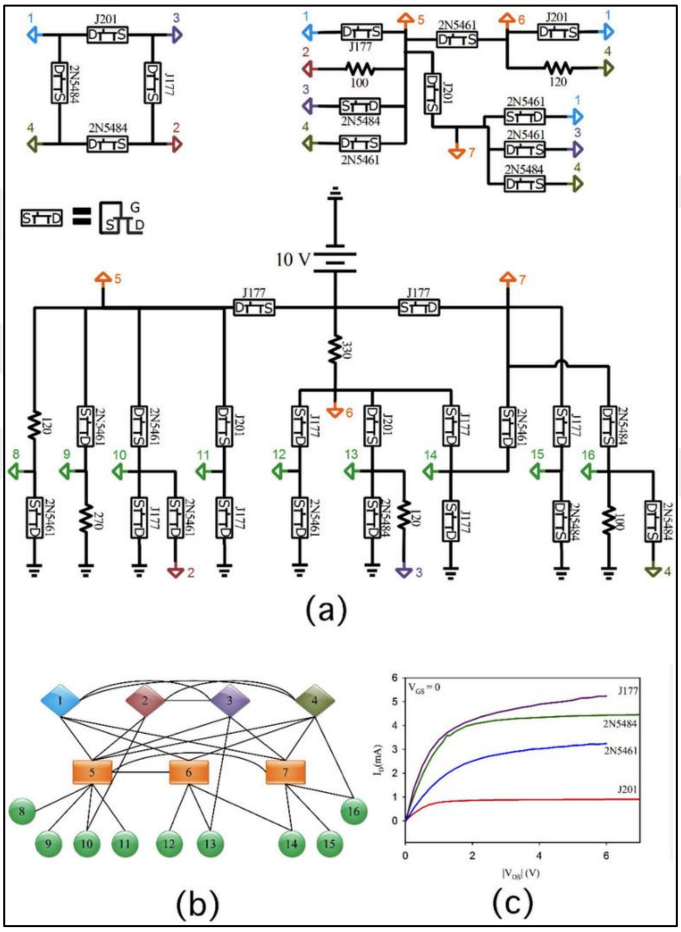

Figure 3.8: AI Control of Electrical Grids [59].

c. Protection of electrical networks

i. Adaptive Protection

Of course, some power outages are unavoidable; strategies must be developed to restore power as quickly as possible and at minimum cost after such events. Even if pre-calculated restoration strategies obtained from simulation studies exist, they are often inadequate because the actual state of the system is quite different from that assumed in the planning studies. In real time, PMUs provide an excellent opportunity to determine a restoration strategy that takes into account the current and real state of the WAMS [60]). A concrete application of PMUs was made in the restoration of the network during the European mega blackout of November 4, 2006 [61].

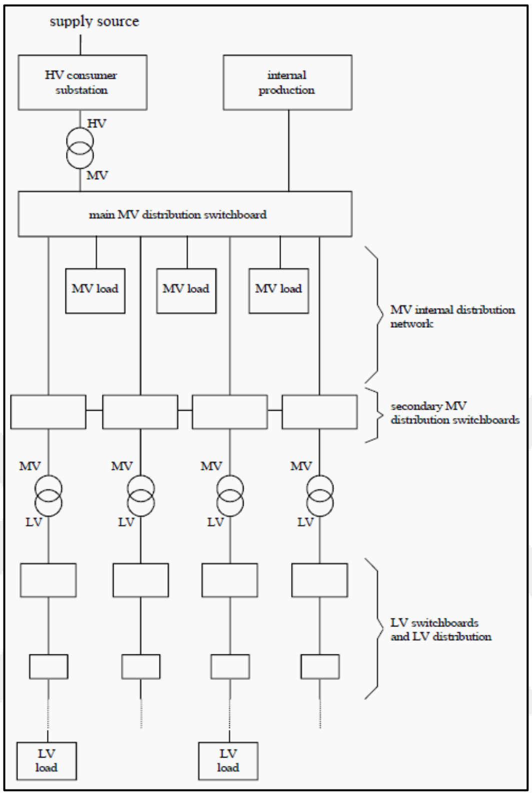

Figure 3.9: Protection Scheme of Electrical Grids [61].

It is also accepted in the literature that a group of generators, called critical generators [62] can cause the complete collapse of the network. Synchrophase measurements can be used to track their behavior and ipso facto feed precise algorithms with data to alert potential anomalies. In this vein, in Chapter 6 of this thesis, we developed a new notion and proposed new real-time instability prediction indices based on PMUs.

ii. Intelligent islanding and load shedding

The use of SIPS is necessary in order to successfully complete islanding [63]. In general, it was designed with the data that was produced from the simulation, but there were some exceptions. As a consequence of this, the performance may not be as good as it could be given the state that the network is in at the moment. PMUs are able to provide a clearer picture of whether the network is heading towards an unstable state (detection and fault location) and whether or not the network needs to be separated to prevent a power outage.

The use of PMUs is one way to get around the fact that the data are not particularly precise. Electricity (problem addressed in the context of this thesis). This specific kind of problem is discussed in this article [64], which also includes the authors' suggestions for indicators that can be used for classifying the extent to which a variety of different contingencies may occur. A person can also determine the optimal boundaries for islanding by basing their decision on the current conditions of the network. This is another way to figure out the optimal boundaries. For example, it is necessary to determine which generator groups will be split up because of a loss of synchronism and how to achieve the optimal load-to-generation ratio in each island that is formed by coherent generator groups and loads. Additionally, it is necessary to determine which generator groups will be split up because of the loss of synchronism. The Electric Power Research Institute (EPRI) has developed a tool [65] that is capable of calculating real-time voltage stability margin indices for a particular busbar or for a specific region by making use of the data collected from PMUs. This can be done for a particular region or for a specific busbar. Because of this, it is now feasible to, among other things, carry out voltage stability studies off-line after particular disturbances have taken place. 2016) that is capable of calculating real-time voltage stability margin indices for a given region or for a specific busbar using data from PMUs. This calculation can be done for an entire busbar or for a specific region. These indices can be computed for the whole grid or for just one busbar at a time. Because of this, it is now feasible to, among other things, carry out voltage stability studies off-line after particular disturbances have taken place. 2016) that is capable of calculating real-time voltage stability margin indices for a given region or for a specific busbar using data from PMUs. This calculation can be done for an entire busbar or for a specific region. These indices can be computed for the whole grid or for just one busbar at a time. Because of this, it is now feasible to, among other things, carry out voltage stability studies off-line after particular disturbances have taken place. In a similar vein, it is possible to devise a strategy that would deal with the problem of shedding before the frequency begins to degrade, or before the voltage begins a plunge into unstable territory. This could be done either before the voltage begins to drop into unstable territory or before the frequency begins to drop. [66]

3.6 CONCLUSION

In this chapter, we looked at the terminology and vocabulary used in the analysis and evaluation of the stability of electrical networks. The notion of stability has been defined in a general framework and also in the specific context of electrical networks. The various ramifications of stability are discussed. The difference between safety, reliability and stability of electrical networks has been clearly established. Mathematical and theoretical concepts of synchronous machines related to the study of transient stability are also provided. In the last section, we addressed the different modes of operation of electrical networks that play an important role in the study of stability.

4. PROPOSED METHOD

This chapter covers the steps involved in machine learning, including data collection, preprocessing, and model construction. In this chapter, we go into detail about the thought process that went into our methodological choices. This chapter can, to some extent, be used as a guide or model for the creation of other models that are similar. The type of information that is being analyzed ought to direct both the selection of methodology and the subsequent application of that methodology. The technical approach that was taken in this chapter is illustrated in figure 4.1 for your viewing pleasure. Below you will find a detailed explanation of the entire process, beginning with the retrieval of data and ending with the implementation of ML algorithms.

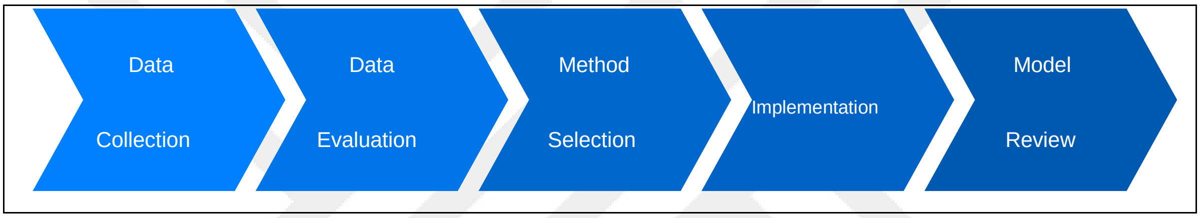

Figure 4.1: Visualization of the Main Tasks Included in the Technical Approach.

4.1 DATA COLLECTION

Within this section, we will discuss the process that was followed in order to gather the data. When we first started working with the data set, we had only a limited understanding of what it contained. In addition, we lacked a comprehensive comprehension of the data sources that were going to be available to us. We reached out to a variety of DSOs in order to compile the necessary information for this report. As a consequence of this, we reached out to a variety of different DSOs in the hopes that at least one of them would have access to grid data that they could share with us. A DSO that is currently in the process of implementing a pilot project in approximately 30 of their substations is the one that gathered the information that was used in this report. A number of sensors have been installed in each of these substations by the DSO so that they can keep an eye on the machinery that is housed within them. In addition, taking into account the fact that this DSO spends more than ten million Norwegian Krone annually on CENS to cover unscheduled outages, it stands to reason that the statistics they collect must contain some inaccuracies. On the other hand, during the course of the previous year, only two of the substations that had sensors installed in them experienced a problem with their functionality. Following discussion, we came to the conclusion that additional investigation into the data collected from these substations is warranted. In addition, the fault records that are generated by their SCADA system are extremely helpful. Following a series of productive exchanges with them in the form of semistructured interviews, we came to the conclusion that it would be in our best interest to sign a nondisclosure agreement with one of the DSOs. Both of the S-series substations have on two separate occasions provided us with information that was inaccurate. (S1 and S2). Measurements were taken with a resolution of one minute for each of the 24 hours' worth of data that were sent over in the data set that was sent over. We thought that it might be helpful to have more faults and longer intervals of continuous measurements while the substation is operating normally, so we asked for data from other times in S1 and S2 because we could use that information. The request also included specifics regarding the failures that had already been encountered in the datasets that were received along with their underlying causes. In addition, this information was included in the request. When the DSO used their SCADA systems to attempt to export additional data from substations S1 and S2, they ran into some technical difficulties. At some point in the future, substation S3 provided us with a dataset that included a year's worth of aggregated measurements that were collected on an hourly basis. The DSO was able to offer illuminating commentary concerning the technical underpinnings of the data. It is not completely out of the question that exogenous factors, such as information on the weather, could have an effect on the state of the components that are responsible for the operation of the power grid. The falling of trees and other types of vegetation as a result of the wind can be a cause of disruptions, and precipitation, particularly rain and snow, may have an effect on underground power cables. The load that is placed on the power grid is affected by the weather in a different way. Because of this, we have incorporated the data on wind speed and precipitation that was gathered at weather stations that are located in close proximity to the substations. These weather stations are located in close proximity to the substations. Freely accessible to the general public and presented in JSON format, the Norwegian Meteorological Institute's weather data can be accessed through the institute's application programming interface (API), which is a RESTful implementation. You will have access to "quality controlled daily, monthly, and yearly measurements of temperature, precipitation, and wind data" if you use the application programming interface (API). Because we needed API credentials, we went ahead and made a user for ourselves. By reading the API documentation, we were able to acquire the knowledge necessary to retrieve data from weather stations by making HTTP requests that were programmed in Python [metb]. We tracked down the weather stations that were physically situated in the most immediate proximity to the substations of interest and pored over the data that these stations made available to us. Not all of these weather stations had data on the amount of precipitation that fell as well as the wind speed that prevailed during the relevant time periods. As a consequence of this, we had to retrieve the data regarding the rainfall from one weather station and the data regarding the wind from a different weather station.

4.2 DATA CHARACTERISTICS

We investigate data characteristics to find useful traits for our purpose. Data characteristics are significant in the phase of algorithm selection. The purpose and importance of different measurements in the dataset should also be understood. Due to limited domain knowledge, this too is part of investigating the data characteristics. This section presents the most significant characteristics discovered during the inspection of the data. In total, we received data containing sensor measurements from three substations. From one of the substations, S3, we received hourly aggregated values from the year 2018. However, no faults occurred in S3 during 2018. For substations S1 and S2, we received measurements, as well as event logs. The data covered two specific dates, October 27th, 2018 and January 1st, 2019. S1 and S2 experienced failures resulting in outages on both of these dates. Table 4.1 summarizes the characteristics of the received datasets.

Table 4.1: Contextualization of Substation Data.

	S1	*S2*	*S3*	**Shared**
Data Interval	27.10.2018 & 01.01.2018	27.10.2018 & 01.01.2018	09.01.2018 - 31.12.2018	-
Resolution	Every minute	Every minute	Every hour	-
Event logs included	Yes	Yes	No	-
Faulty days	2	2	0	-
Sensors measuring voltage	30	24	36	24
Sensors measuring current	15	12	18	6
Sensors measuring power	5	4	6	4
Sensors measuring volt-ampere	12	9	14	8

The datasets that were collected from the S1 and S2 substations are extremely comparable to one another, as can be seen in Table 4.1. This is especially true in terms of the data interval, resolution, and number of days with errors in the datasets. The data collected at Substation S3 are very different from those collected at S1 and S2. In addition, the number of sensors that measure voltage, current, and power in a given substation is specific to that particular substation and cannot be found in any other substation. In addition, the voltage of the feeders for S1 and S2 is 22 kilovolts, whereas the voltage of the feeders for S3 is only 11 kilovolts. The datasets that were used in the papers that were discussed in the Chapter on Related Work contain anywhere from 277 all the way up to 2438 errors. This range of errors was found in the datasets. On the other hand, there are a grand total of only eight failures in the datasets that we have obtained up until this point in time. [Citation needed] Table 4.3 provides a breakdown of the failures that occurred in both Stage 1 and Stage 2. The fact that our dataset has such a low number of instances of outliers has the potential to make the level of uncertainty that is associated with our findings greater. When we looked at each measurement in greater detail, we found that some of the values were zero across the board in the dataset that we were analyzing. This became clear once we broke down each measurement and analyzed it on its own. Sensors that are not active are represented by values of zero in the data set. In addition, several of the sensors produced lengthy sequences of repeating values, despite the fact that the variables from which the values originated were continuous. This was despite the fact that the values originated from continuous variables. In some of the sequences, the values would continue to cycle for a period of up to three minutes at a time. The DSO offered an explanation as to why this is the case and stated that it is due to the fact that the SCADA system will not report a change in measured value unless it is greater than a previously established threshold. The DSO provided this explanation in order to shed light on why this is the case. It was found out that some of the parameters are comparable between the various substations, and this was discovered. It would appear that the three substations' total of 24 voltage sensors and 6 current sensors are all measuring the same things in the same manner. It would appear that there are four units that are equivalent to one another when measuring power, whereas there are eight units that are equivalent to one another when measuring volt-ampere. It appeared as though all of the power and volt-ampere measurements that were taken in S1 and S2 were statistically distinct from their counterparts that were taken in S3, both in terms of amplitude and variance. Between May 25 and August 17, there is not a single observable shift in any of the values that are contained within the S3 dataset. Because of this reason, we reasoned that it would be prudent to leave this time period out of the analysis. This was the conclusion that we arrived at. There was a disparity between the three substations in terms of both the resolution and the length of the data that was transmitted. To provide a brief summary, the datasets S1 and S2 only contain measurements for a single day, whereas the dataset S3 contains information that was gathered over a longer period of time. Although the readings from S1 and S2 are derived from instances in which faults and outages were officially reported, the readings from S3 are always accurate because it was functioning normally throughout the entirety of the time frame that is being investigated.

4.3 SELECTION OF MACHINE LEARNING METHOD

Before diving into the data that was sent to us, our plan was to first adopt the strategy that was used by the majority of the papers in Section 3. This was our intention before we started digging into the data. The experiments that were described in these papers made use of data that was not only riddled with inaccuracies but also encompassed significantly longer time periods than what would have been suitable. When faced with challenges similar to these, it is possible to construct accurate prediction models through the application of supervised learning strategies. The examination of the data showed that S3 had a longer stretch of only normal condition data when compared to S1 and S2, which had shorter stretches of data that were inaccurate. This was the case in contrast to S3, which had a longer stretch of only normal condition data. We had no choice but to rethink our strategy in light of this development. In the prior section (2.4), we discussed how unsupervised learning can be used in a variety of settings, one of which is the identification of outliers within a dataset. Another setting in which unsupervised learning can be utilized is in the prediction of future events. Unsupervised learning has many applications, and this is just one example of one of those applications. Because our data, particularly from S3, contains extended windows with many examples of the same class—namely, the normal condition of the substation—we decided to also investigate unsupervised learning. This decision was made because our data contains extended windows with many examples of the same class. Because our data contains extended windows, we decided to proceed in this direction.

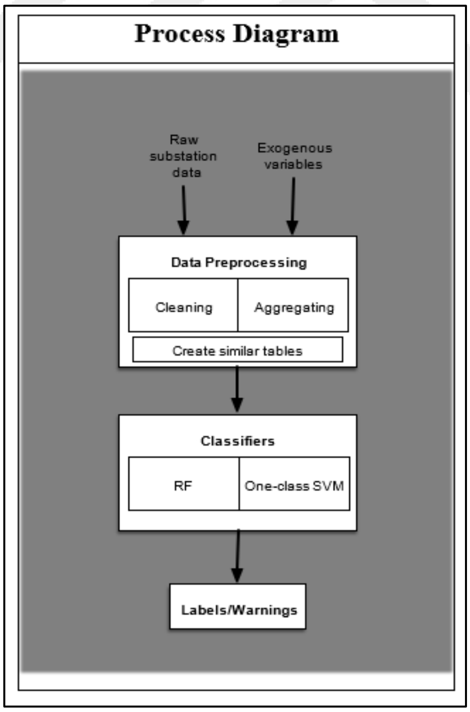

Figure 4.2: Process Diagram.

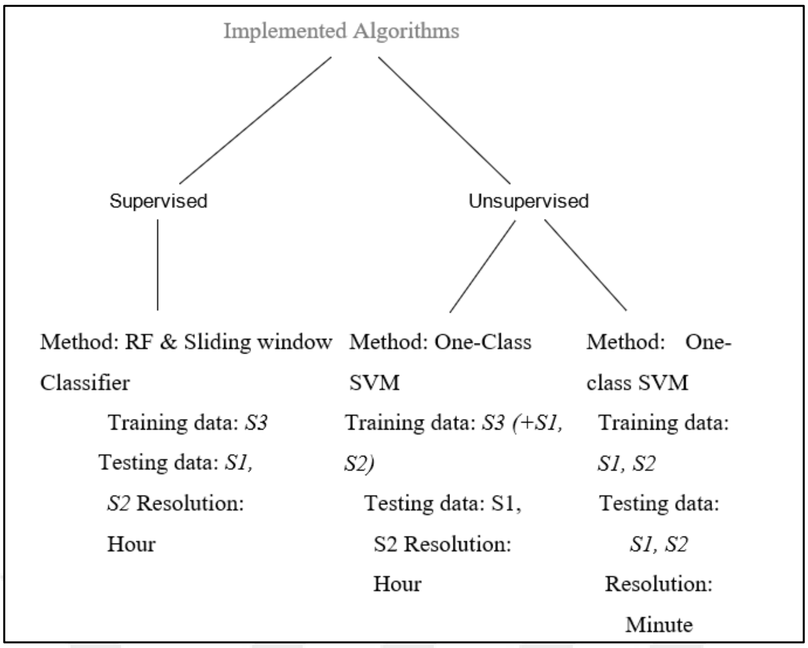

Figure 4.3: One Supervised and Two Unsupervised Approaches to Algorithms Were Tested.

4.4 THE SUPERVISED IMPLEMENTATION

A supervised-learning method was the initial strategy put into action. The goal of this method was to train a model using historical data from a single substation. The goal in developing the model was to identify potential failure points by spotting recurring patterns. Unfortunately, the small sample sizes meant that we had to combine data from S1 and S2 several times before arriving at the final S3 dataset. The purpose of this was to show how an ML algorithm would be implemented on a substation that had experienced a significant number of outages during the measurement period. Therefore, rather than an attempt to achieve robust results, the presented supervised approach provides a framework for future similar work on how to implement such an algorithm.

4.4.1 Data Preprocessing

The preprocessing stage of a machine learning project is typically regarded as the phase that poses the greatest degree of difficulty due to the nature of the context and the work that is associated with it. As a part of the preliminary work for the supervised method, the following were included: The first thing that happens is that the data set is loaded. Second, aggregation of S1 and S2 into hourly measurements, followed by transformation of the data into a dataset that is analogous to S3 by tabularization of features that are analogous to those in S3 that are relevant. This step is followed by transformation of the data into a dataset that is analogous to S3. Third, creating S3 by merging the datasets from S1 and S2 into a single document. The exogenous variables need to be gathered and recorded in a table as the fourth step of the process. (3). In the absence of data, appropriate action should be taken. Mark each separate piece of information with a unique label so that it can be located quickly. Adjusting the size of the features is the seventh step. 8. Using the information in the table, compile two different collections of data: a test set and a training set. In order for us to be able to import the Excel files into Spyder, we first had to convert them to a format that utilized commas as the delimiter between each of the values. (IDE). Following that, we differentiated between the power and voltage readings from S1, S2, and S3, in that order. Three different readings of electric current were taken at low voltage (400V), eighteen different readings were taken at high voltage (22kV), and a total of six readings were taken. We aggregated the minute values from each dataset into hourly aggregated minimum and maximum values in order to make the tables in S1 and S2 comparable to the one in S3. This was done so that the tables in S3 would be easier to understand. This was done in order to facilitate comparisons between the tables and the table in S3. In order to simulate a substation that had multiple failures over the course of a longer measurement period, we combined the data from Tables S1 and S2 along with the measurements from Table S3 to create a single table. This allowed us to simulate the substation. In the S3 dataset that we developed, there are a total of ten new faults that were included. The S3 table has been modified to include a total of ten faults, as well as the hourly minimum and maximum values for the data spanning a few months' worth of time. This change was made. After that, the weather variables that had previously been retrieved were incorporated into the model. By taking the column's average, we were able to fill in the spaces where there was a gap in the weather data by using that column's average. Labeling the data is a necessary step that must be completed before a supervised model can be trained on the data. We use a technique known as sliding window classification to categorize records according to the likelihood of an error occurring within the next hour. We give a row the value of "1" if a fault occurs within the next hour, but we give it the value of "0" if there isn't any fault that occurs within the next hour (as can be seen in Figure 4.4). Feature windowLabel window.

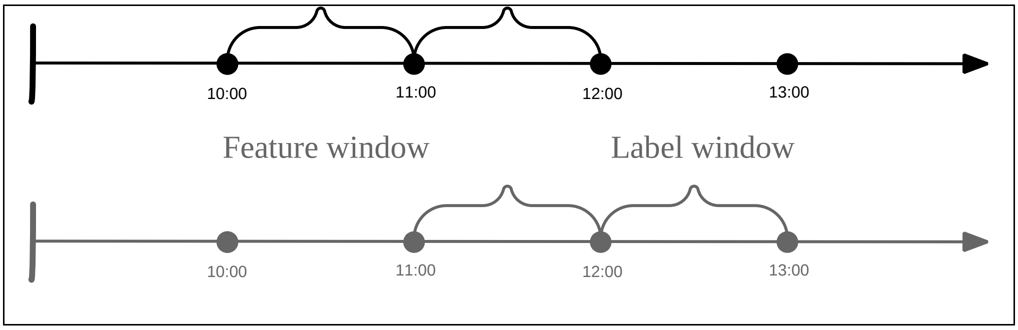

Figure 4.4: Sliding Window.

After that, the information was "feature scaled" or "normalized" within a specific range that had been established beforehand. You are able to calculate the grade distribution. Where u is the mean of all the samples used for training and s is the standard deviation of those samples. The primary reason for making this adjustment is to avoid situations in which characteristics that have narrower numerical ranges are overlooked in the shuffle. After that, we created a training set and a test set by partitioning the table into two groups that did not overlap with one another. On November 1st, the data were split into two sets: one for training purposes, which included data from January 9th through November, and another for testing purposes, which included data from November and December. When the model has been constructed with the help of the training set, it is then put to the test using the test set by making predictions using that set. When the times when measurements are frozen are taken out of the equation, 70% of the data is utilized for training, while the remaining 30% is utilized for testing).

4.4.2 Predictions

It is now possible to try to predict whether a fault will occur within the next hour by using a model that has been trained on historical data to learn to recognize patterns (if there are any) occurring before a grid failure. To make these sorts of forecasts, we use RF classification.

4.5 THE UNSUPERVISED IMPLEMENTATION

When contrasted with the supervised method, the unsupervised methods stand out as being particularly distinctive. One of the most significant distinctions is that the data were not labeled before the unsupervised procedures were used to train the model. This was one of the factors that contributed to the accuracy of the results. With the knowledge that we had at our disposal, we put into action two different strategies that did not require any form of supervision. The first step in our unsupervised process involves training the model using the S3 dataset, which is perfect and does not have any mistakes. The second technique is an unsupervised one that takes into account the variations in levels that are specific to each individual substation. Because we trained a model with One-Class SVM on the typical patterns seen in substations that were operating correctly, we were able to identify readings that were outside of the normal range. This allowed us to identify readings that were outside of the normal range. The concept of "One-Class SVM" is dissected and discussed in greater depth in the section of the article titled "One-Class SVM." The first unsupervised method that we use involves aggregating the hourly minimum and maximum values from S1, S2, and S3, as well as the climate data, and then training a model with these samples. The second unsupervised method that we use involves aggregating the hourly minimum and maximum values from S1, S2, and S3. The second unsupervised method involves the training of two separate models using data obtained directly from the substation. One of the models is designed for S1, and the other is designed for S2. The training process makes use of these data in various ways. Following this, we will discuss in greater detail two unsupervised methodologies that we have put into practice. Both of these methodologies were developed by us.

4.5.1 Data Preprocessing for Unsupervised Learning

Before we created the training set for the unsupervised method, we preprocessed the S3 dataset to include measurements of current and voltage. This was done before we created the training set itself. After that, in order to bring this process to a close, we added data to this table regarding the wind and the precipitation. After that, in order to serve as test cases, a total of four tables were crafted, two of which were from the 27th of October, 2018 (S1 and S2), and two of which were from the 1st of January, 2019. (S1 and S2). We were given granular readings of voltage and current for days when the grid was down, and those readings were included in both the S1 and S2 data sets. During the days when the grid was down, we were provided with those readings. We added data on wind and precipitation, as well as aggregated the minute measurements into hourly minimum and maximum values, in order to make the test sets more comparable to the training set that was found in S3.

By utilizing the S1 and S2 datasets, which each have a resolution of one minute, our second unsupervised method allows us to investigate the effect of training and testing on shorter intervals. Specifically, we look at how this affects the accuracy of the model. In addition, in this method, as can be seen in Figures 4.5 and 4.6, we only test a model by using data from the same substation as the data that was used for training it. This is because testing a model with data from a different substation would be meaningless. The figures clearly demonstrate this point. Either of the two approaches that were just described could end up being ineffective due to the wide variety of characteristics that can be found in substations. Those characteristics include: This effect, which is brought on by substations that are one-of-a-kind, can be eliminated by using the second unsupervised method because each model that is constructed uses data from just that one substation. The second unsupervised method, like the first, selected current, voltage, and temperature as its primary distinguishing characteristics. However, wind and precipitation data are absent from the tables in the second unsupervised method because we were unable to retrieve weather information at such a fine resolution. This is due to the fact that the tables were generated using the unsupervised method that came first.

The second unsupervised method involves dividing the data into training and test sets according to the frequency of failure in each of the S1 and S2 datasets. This method does not involve a supervisor monitoring the process. The first unsupervised method can be thought of as having been extended using this method. A timeline, which can be seen in Figure 4.6, illustrates the interval of time that exists between training and testing. Data are added to the training set starting a few hours before the fault occurred and continuing for up to three hours after it took place. This process continues until all available data have been added. We made the assumption that measurements taken at the time of the failure might not accurately reflect the substation's normal state, so in order to account for this possibility, we inserted an artificial delay in the middle of the training set. The information gathered in the test set covers a period of time that begins approximately three hours before the failure and continues all the way up until the time that the failure actually took place. This time period is referred to as the "coverage period." In addition to training and testing windows, a summary of the failure occurrences that occurred across all datasets is presented in Table 4.2.

Table 4.2: Failure Times, Training Sets, and Testing Sets Used in the Second Unsupervised Approach.

	S1(27.10.18)	*S2*(27.10.18)	*S1*(01.01.19)	*S2*(01.01.19)
Faults	12:34 - 12:40	12:34 - 12:40	10:33 - 10:35, 11:01 - 12:07, 14:50 - 14:51	10:33 - 10:35, 11:01 - 12:07, 14:50 - 14:51
Training set	00:00 - 09:59, 18:00 - 23:59	00:00 - 07:59, 15:00 - 23:59	00:00 - 03:29, 18:00 - 23:59	00:00 - 07:59, 16:00 - 23:59
Test set	10:00 - 17:59	09:00 - 14:59	08:00 - 15:59	08:00 - 15:59

Table 4.2 details errors that were gleaned from the DSO's event logs. By hand, we found fluctuations in some of the datasets that might point to unexpected activity. There is no indication of this behavior in the system's event logs. We have used slightly different lengths of training and testing intervals so as to avoid including these variations in the training sets. Therefore, the smallest test set contains 25% of its total dataset, and the largest test set contains 33.3% of its total dataset.

Table 4.3: Parameters Used for the One-Class SVM.

One-Class SVM Parameters	**Value**
NU	0.05
Cache Size	200
Degree	3
Kernel projection parameter (coef0)	0.0
Gamma	Scale
Kernel	RBF
Maximum iterations	-1
Random state	None
Shrinking	True
Tolerance	0.001
Verbose	False

In the following table, Table 4.3, you'll find a rundown of the default settings for the vast majority of the Scikit-learn library's parameters. The maximum iteration, along with NU, Gamma, and Kernel, are among the most significant of all the iterations. The NU parameter establishes a ceiling for the total number of errors that were made all the way through the training procedure. We came to the conclusion that a value of 0.05 for the NU parameter would give us the best chance of ensuring that a maximum of 5% of the training examples would be absent from the hypersphere that would be used for classification. A true positive occurs when a model determines that an observation is flawed and, within the space of an hour, the failure actually takes place. This is called a confirmation of the model's prediction. However, the prediction is regarded as having been incorrect if the failure that was forecasted did not occur within the hour that followed the hour in which it was predicted to occur. When a model projects that a failure will not take place within the next hour, but then a failure does take place within that time frame, this type of prediction is referred to as a false negative prediction. [Case in point] When the model correctly predicts that a failure will not occur within the next hour, this is an example of a true negative prediction. A true negative prediction is one in which the outcome is not the one that was anticipated.

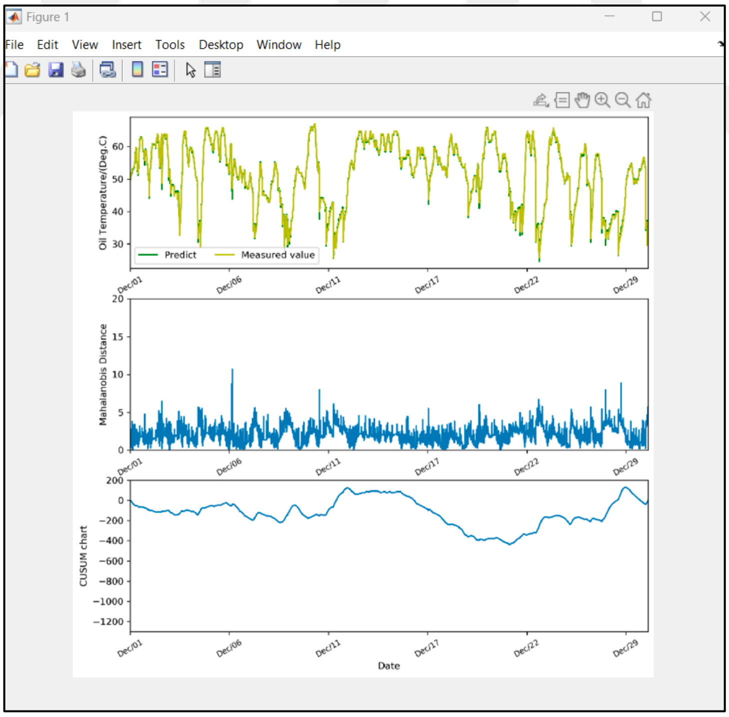

Figure 4.5: Predicted Failures in the Proposed System.

When utilizing unsupervised methods, on the other hand, it is a great deal more challenging to determine whether or not an anomaly detection is accurate. Because the models are only trained to identify outliers, the unsupervised methods are unable to provide an accurate prediction of when a failure will take place. This is because of the nature of the training. In the event that an anomaly is found, this may suggest that the substation is in a condition where the likelihood of it failing is higher than it would normally be. The underlying cause of the failure has a direct proportional relationship to the degree of success that can be achieved in spotting warning signs in advance. It is impossible for us to put a human stamp of approval on the question of whether or not the condition that an observation represents is normal because we do not know what is going on beneath the surface. This prevents us from being able to answer affirmatively yes or no to the question. As a direct result of this, there is no concrete class that is capable of accurately capturing the state that the substation was in during the observation in question. This is because the substation is a dynamic system that is constantly changing. As a direct result of this, we will present the findings of the unsupervised methods by making use of two distinct methodologies in order to do so.

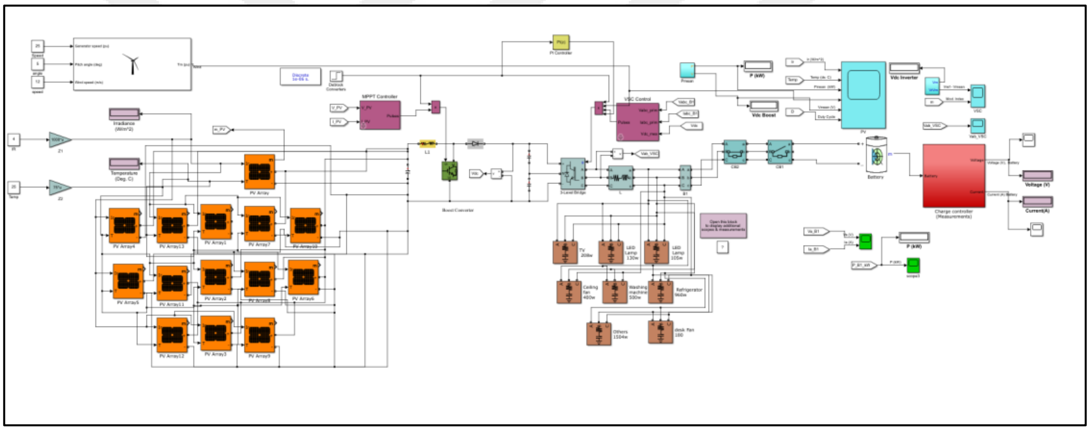

Figure 4.6: The Proposed Model in MATLAB Simulink.

The first tactic entails merely presenting the total number of irregularities found in the period of time leading up to the failure. This is the beginning of the first strategy. In the second method, which counts the number of anomalies that contain statistically significant information, a particular NU parameter is used. A deeper and more in-depth explanation of the two distinct methods is provided in the following sections of this article.

Table 1 presents the total number of classified observations as well as the total number of outliers found in each of the test sets. To get things started, the total number of observations that were classified. The observations that were gathered using the first unsupervised method are segmented into hourly chunks for further analysis. The second method has a resolution of one minute and does not require any supervision while it is being carried out. When compared to the first unsupervised method, the total number of classifications produced by the second unsupervised method is consequently greater than that produced by the first unsupervised method. In the second place, we will discuss the outcomes of the statistical hypothesis testing that were presented in figure 4.7 To begin, we take a look to see if the number of warning signs that were identified immediately prior to a failure is significantly higher than what would be anticipated given the conditions that are typically present. If so, we consider this to be a positive sign. The next thing that needs to be done is to determine whether or not a statistically significant number of irregularities were found just prior to the failure for each of the occurrences. This is the next thing that needs to be done.

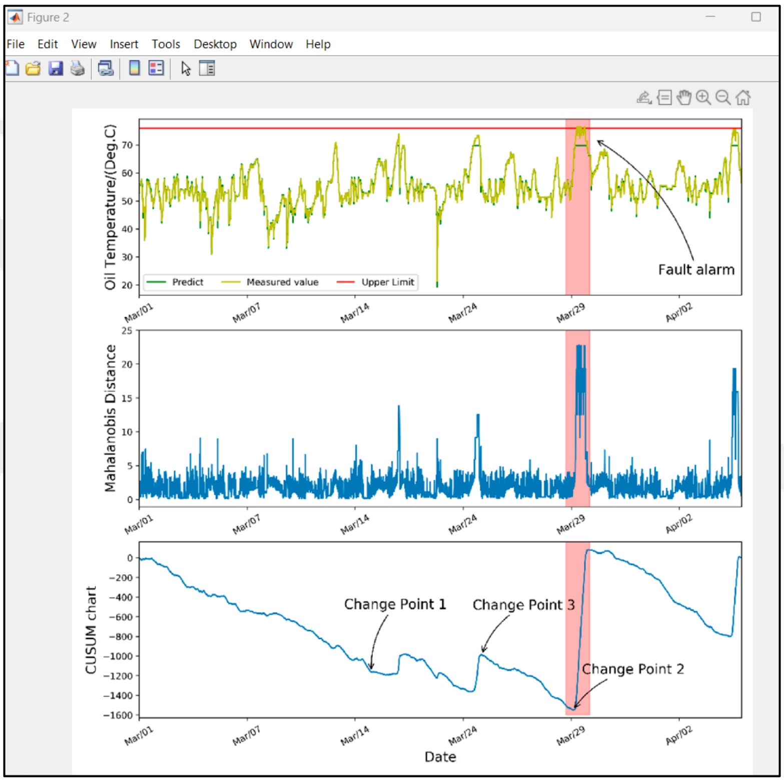

Figure 4.7: Alarm Raised in the Second Model S2 by the SVM.

The hypothesis predicts that, in comparison to times when the system is operating at its optimal level, a greater proportion of observations will be regarded as anomalous just before the failure of the system. This is in contrast to times when the system is operating at its optimal level. This can be shown by counting the number of data points in the test set that are identified as outliers by the model. We put this theory to the test by calculating the odds of encountering that many outliers in the course of a typical series of events and comparing them to the actual number of such occurrences.

5. CONCLUSIONS

The electrical energy distribution system comprises mainly the network with voltages below 13.8 kV, fed by substations, and the step-down transformers that will adjust the voltage for the final consumer to 127 V, 220 V or 380 V depending on the region and the standardization of the concessionaire This system has a very high capillarity and is where the main points of improvement for energy quality and reliability are located. The concept of intelligent energy networks (Intelligent Energy Networks), or Smart Grid (SG) [7] has been developed aiming to make the EPS operation more robust, economical, reliable, available and automated. New technologies, applications and smart devices have been developed, mainly to make the distribution layer smarter. However, an EPS must have an integrated intelligent operation, aggregating all functionalities at all levels of the EPS with the aim of improving the EPS's performance in terms of economics, quality of service and technology. The use of these resources makes it possible to make the operation of the electrical system more flexible in the contexts of generation, transmission and distribution, reaching new levels of quality for these services. One of the main impacts that EPS have on current systems is in the context of energy generation. There are often opportunities for generation on a smaller scale and distributed throughout the EPS. All the assumptions of an EPS are based on the autonomous behavior of its subsystems. Actions such as detection and isolation of faults, electronic negotiation of purchase and sale of electricity, determination of fraud and reconfiguration of distribution networks, among others, must be carried out autonomously, actively, so that the network can anticipate problems and thus display intelligent behavior. Based on robust prediction methods, the various agents present in the system may have learning and anticipation capabilities, thus implementing a completely autonomous and intelligent system. Several methods of prediction and machine learning are implemented in current electrical systems. All these methods are adapted to the reality of large interconnected systems and their classical energy sources. With the development of Smart Energy Grids (SEG), new methods adapted to this new reality are required. REIs have a large share of Distributed Energy Sources (DES) and an active negotiation between energy producers and consumers. Therefore, methods capable of making predictions in a short period of time based on time series that exhibit dependence on long memory are essential. This work intends to contribute in the research area of prediction methods for Long Memory Time Series. Classical methods in the area will be presented and discussed. With this, new proposals with a view to the efficiency and accuracy of the algorithms will be made.

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