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MANAGEMENT OF HYBRID ELECTRIC MICROGRID USING FUZZY LOGIC AND ADAPTIVE NEURAL NETWORK

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Master's Thesis

Supervisor

Prof.Dr. Galip CANSEVER

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The thesis titled MANAGEMENT OF HYBRID ELECTRIC MICROGRID USING FUZZY LOGIC AND ADAPTIVE NEURAL NETWORK PREPARED prepared by IHSAN BASIL HASAN AL-JANABI and submitted on 20/5/2022 has been **accepted unanimously** for the degree of Master of Science in Electrical and Computer Engineering.

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Ihsan Basil Hasan AL-JANABI

Signature

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I dedicate this work to my family and friends, and I wish to thank them for all their support, I would also like to thank my supervisor Professor Galip Cansever for his guidance.

ABSTRACT

MANAGEMENT OF HYBRID ELECTRIC MICROGRID USING FUZZY LOGIC AND ADAPTIVE NEURAL NETWORK

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The Energy most countries installed a distributed generation micro-grid which incorporates renewable resources (solar and wind energy) With respect to this system, in this work two topics are addressed; the calculation of the range in which the demand can move and the effect that the demand management signals have on the forecast. For the first topic, fuzzy intervals will be used to determine, based on historical data, the dynamic range. This range provides the limits to the optimizer for the load displacement factor, on which the signals that are sent to the consumers depend.

Keywords: Smart Grid, Fuzzy Logic, ANN, ANFIS

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ABBREVIATIONS

AI	:	Artificial Intelligence
EMS	:	Energy Management System
DERs	:	Distributed Energy Resources
PF	:	Participation Factors
WES	:	Wind Energy System
WNN	:	Wavelets Neural Network

1. INTRODUCTION

1.1 BACKGROUND

Due to the geographical conditions of most countries, there are still communities isolated from the four electrical systems that distribute energy within the country. Smart micro-grids based on renewable energies represent a solution to this problem, taking into account the abundance of resources that exist to generate non-conventional renewable energies. With this in mind, the Energy most countries installed a distributed generation micro-grid which incorporates renewable resources (solar and wind energy). Before the installation of the microgrid, these countries had only 10 hours of daily power, a situation that changed, currently having electricity 24 hours a day. The installed microgrid currently operates with an energy management system EMS which dispatches the units, minimizing generation costs. The EMS inputs are consumption prediction, prediction of climatic variables and the state of charge of the batteries:

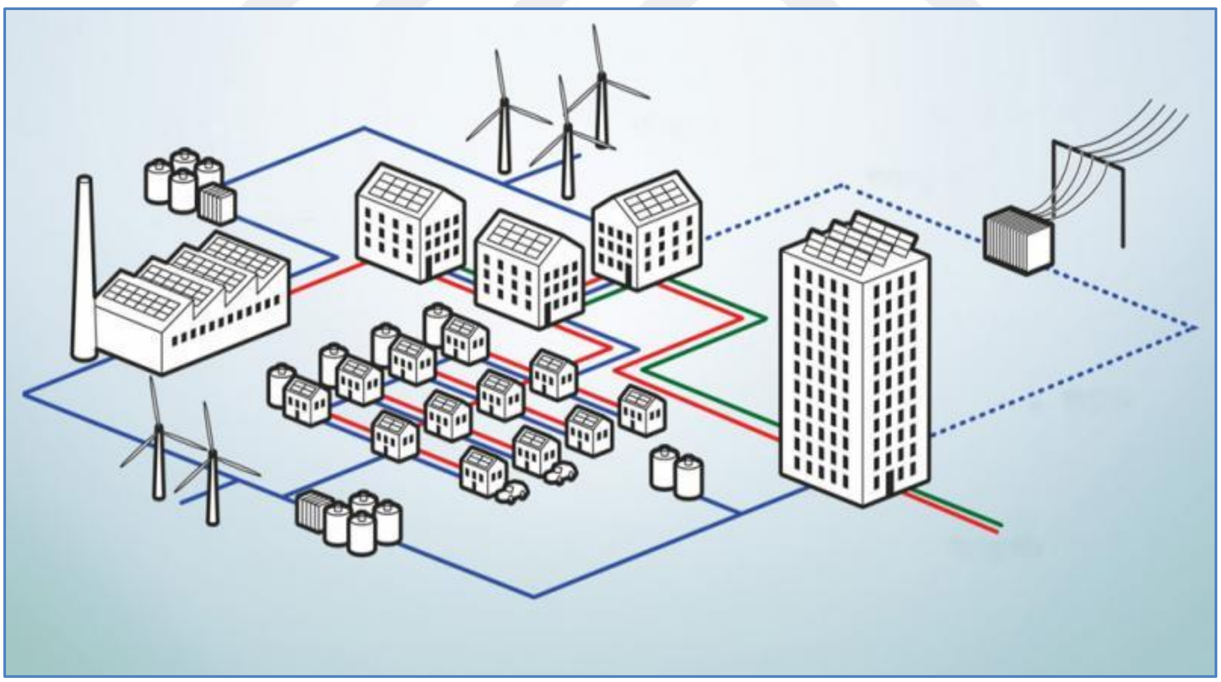


Figure 1. 1: Distributed Energy Storage Systems

1.2 PROBLEM STATEMENT

EMS has a built-in demand management system, based on “demand response”. This system consists of sending light signals to consumers through traffic lights installed in their homes, in order to reduce, increase or maintain their consumption in order to have an optimal dispatch. With respect to this system, in this work two topics are addressed; the calculation of the range in which the demand can move and the effect that the demand management signals have on the forecast. For the first topic, fuzzy intervals will be used to determine, based on historical data, the dynamic range. This range provides the limits to the optimizer for the load displacement factor, on which the signals that are sent to the consumers depend.

The second issue is based on the fact that consumers are expected to modify their consumption when seeing demand management signals, but it is not known by how much, which also affects prediction, which is why a methodology will be presented to model consumption variation using fuzzy Mamdani models.

Demand management strategies serve to maintain the balance between generation and demand, which is of vital importance for micro-grids, where energy resources fluctuate. Also, to maintain this balance, it is important to have a reliable demand prediction, so a model for this will also be performed, using Takagi and Sugeno fuzzy modeling.

In addition, to the typical identification stages, a stability analysis block was added based on the study of the state matrices generated by each fuzzy rule.

1.3 MOTIVATION

Photovoltaic systems are basically made up of a solar panel or an arrangement thereof, a battery, a charge regulator for the battery and, if alternating current is required, a DC / AC inverter. DC / AC inverters are devices that fulfil the function of adapting electrical signals to the conditions required to achieve energy injection, these devices are very useful in automobiles in applications such as cell phone charging, installation of sound plants. and video, and other devices which work with alternating current [4] [5].

For the design of an inverter, very important aspects must be taken into account such as: power, frequency and the different devices with which it will be confirmed. There are two types of single-phase and three-phase inverters, which for their design can be used devices with controlled activation such as BJT, MOSFET, IGBT, MCT, SIT, GTO.

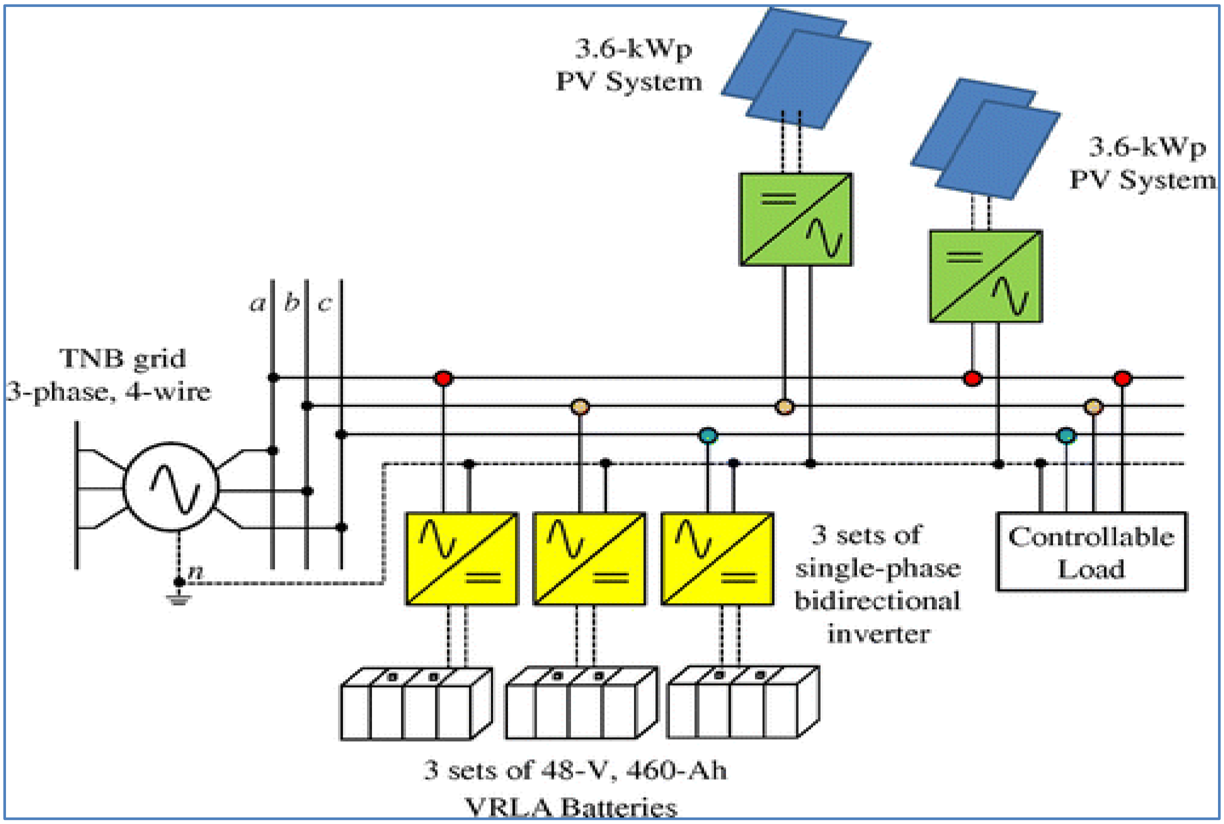


Figure 1. 2: PV Hybrid Electrical Systems

1.4 CONTRIBUTION

The components and control mechanisms under inquiry are presented in this dissertation's theoretical framework. Additionally, the methodology section contains information on the elements and techniques that were used to arrive at the results, which are then provided in the next section. This study makes use of fuzzy logic to demonstrate the advantages of smart grid voltage control in a steady state context. The purpose of this inquiry is to establish what happens when the voltages at the nodes are shifted by more than 5% of their normal range due to events such as line disconnection, increased load, decreased load, and other causes. The final draft of the report includes a summary of the results and conclusions of the inquiry, as well as recommendations.

1.5 THESIS STRACTURES

The thesis is structured as follows: Section 2 is where we review some of the previous work and implementation on smart grids. Section 3 is where we give a background about all the components. Section 4 is where we explain our model in details and implementation of that model in details, Section 5 is where we simulate our model and record the results obtained. Section 6 is where we conclude our work and put a future scope into perspective.

2. THEORETICAL BACKGROUND AND LITRITAURE REVIEW

2.1 CHAPTER AIMS

The purpose of this chapter is to describe earlier classifications of network malware with the goal of obtaining solutions that may be applied to the present situation, which is a difficult endeavour. The objective is to establish whether or not the system has been compromised or whether or not malicious software has been used when the system is operating normally. Traditional generators, which store kinetic energy, provide the rotational inertia for the rotor shaft. The generator's rotational speed has a direct effect on the electrical distribution system's frequency. The greater a power system's rotational inertia, the more stable it is believed to be. Renewable energy deployment on the grid has increased in recent years. The use of power converters to incorporate these resources into the grid does not imply that the system gains rotational inertia. If distributed energy resources (DERs) are not properly regulated, they have the potential to produce instability. To address this, the DER's controllers will need to take on more tasks. Renewable energy sources, when handled properly, may be able to aid with voltage and frequency management. For instance, to offer frequency support, the wind energy system (WES) may vary the amount of active power injected in response to its operating frequency. As a consequence, WES must conserve a certain amount of active power and then utilize it when the frequency is dropped to accomplish this. When a wind farm's active power control (APC) is used in a disturbed environment, a problem occurs. The APC's dynamic reaction requires a short time period. Active power control is composed of several sub-control objectives, the most critical of which are inertia control, primary frequency control (PFC), and automated generation control (AGC). Due to the active power's rapid response time, it is controlled consecutively for a certain amount of time. Wind speed unpredictability may cause problems in the control loop, resulting in the control loop failing to operate correctly. By modifying the basic control algorithms, it is possible to include frequency control into WES systems [1–14]. Numerous control strategies and techniques have been developed to assure the stability of a power system during frequency variations. Control tactics may be classified into two groups based on the degree of control and engagement elicited by control approaches [15–19]. The previously conserved kinetic energy may be used to provide inertial control in a number of scenarios. The turbine's inertia determines how long stored energy may be released for a certain amount of time. To compensate for the inertial response, you must lower the wind turbine's maximum power point. This is technically referred to as a fundamental frequency response (PFC). Wind turbines' present power systems have been extensively researched for possible strategies to include PFC. Numerous research on wind farms have been undertaken, while others have focused on electrical systems (transmission, distribution, and so forth) [20–23]. Another study examined the physical effects of de-powered wind turbines carrying comparable loads to their full-power equivalents. Numerous studies [25–28] have examined the effect of PFCs on wind turbines and the availability of readily available resources. The active power control technique presented in reference [29] conserves energy by using weep and inertial sensors, as well as PFC and AGC. Numerous droop control systems may be utilized to maintain a steady and constant grid frequency. In the preceding reference [30], a droop controller for the WES was discussed in order to improve the generator's responsiveness. When addressing droop, the word "droop" relates only to the WES controller and only on a site-specific basis to a wind farm or smart grid generator. The controller discussed in this article utilizes fuzzy logic to provide frequency support for a smart grid. Wind turbine participation factors (PF) are computed for individual wind turbines by determining whether wind turbines have reserved power and are operating at or near their maximum output capability factor (ROCOF). This is performed by identifying wind turbines that have reserved power and those that are running at or near their maximum output capability factor (ROCOF) (PCC). The architecture of an electrical power system enables the system's response to frequency alterations to be verified.

2.2 SMART GRIDS

A Smart Grid is the cutting-edge technology that will bridge the gap between the electric grid and the digital era. In this manner, the grid may react to changes and make those changes a factor in deciding the price. Since problems, such as transformer failures, or variables that impact demand, such as heat waves, can be handled, the next step is to manage demand-sensitive events, such as heat waves. One of the main forces for its adoption is the likely considerable savings projection of up to $75 billion over the next two decades. Main challenges which have necessitated the need for an efficient grid system were discovered by Wissner et al. [7] The first thing they discovered was the deregulation of power markets, which were tied to the unbundling of previously integrated structures and the appearance of intense competition; next, the remarkable growth of decentralized energy generation, especially with respect to renewable energy; and finally, the important need for energy conservation to help curb global warming. Power generation and distribution automation may be included in the Smart Grid in the form of "ambient intelligence." Information technology may be used to interconnect dispersed, renewable, small-scale power sources. In order to better balance the power flow, broadband connectivity may be used to set up intelligent software that will guide resources automatically. An automation project might significantly expand the capabilities of the electricity transmission and distribution system. On the distribution side, demand and supply adjustment would be managed by software. A smart home that can dynamically balance its power use would be a consequence of communicating electricity usage with smart meters.

Using the grid in a grid network and performing automatic meter reading (AMR) on it, Ja-Rventausta et al. examined the performance of AMR systems. an intelligent piece of equipment is being designed to have a remotely readable energy meter (i.e., an interactive customer gateway). a platform that includes AMR technology and two-way connectivity between databases and applications from the DSO, TSO, service providers, and energy-market actors (e.g., aggregators). A focus of Clastres's research was to identify the policy concerns relating to the Smart Grid. By regulating demand, including renewable resources, and equipping the grid with more efficient storage devices, the Smart Grid improved its performance. It was emphasized, however, that policy issues remained unresolved alongside economic issues. Not just restrictions, but also excess skimming, dynamic pricing, and rules for incorporating new networks are vital among them. Smart Grid simulation systems have been built multiple times throughout the years [10], [11], [12] The authors in [10] simulated a basic microgrid with accuracy by implementing low-level electric circuits functionality using MATLAB and Simulink. In an effort to illustrate that intelligent distributed autonomous systems might function effectively, the authors put up the notion of a micro-grid that is paired with intelligent agents. It was a rather straightforward implementation of their agent. Most of the work was just activating circuit breakers to protect vital loads. While they were using a simplified simulation, the agents' interaction and cooperation were not fully tested, appraised, or analyzed. Their goal was instead to build a micro-grid that can be controlled like the rest of the global grid, but can function independently as a "island" as well. Only one simulation example is described in [11], but the adaptive, self-healing architecture for power grids based on intelligent-agent technologies is offered. A simulation that emulates a dynamic smart city is proposed in [12]. When Dua et al. [13] wanted to install Phasor Measurement Units (PMU) on an electric grid, they used Integer Linear Programming as a decision model. PMUs allow for an accurate power measurement to be synced with time. To discover the smallest number of PMUs required to collect the grid's power information, the authors set out to find it. The authors included a zero injection constraint in their Integer Linear Programming model to guarantee the lowest possible amount of PMUs. Optimal PMU placement has many options, as shown by the research. While the solution with the greatest System Observability Redundancy Index (SORI) yielded the greatest results in their situation, the SORI-enhanced solution yielded the greatest results overall. a decisionmaking model for Unmanned Aerial Vehicles to plan, categorize, attack, and conduct damage assessment on the opponent was developed by Hennebry et al. [14] (UAVs). Creating subteams to concentrate on a single, crucial objective looked more possible for Hennebry et al. Integer Linear Programming succeeded in resolving these particular issues. To see whether the heuristic model's performance was equivalent to the optimum solution, they compared the results. The percentage error was within 0.13% to 0.63% when the sub-teams were used. The heuristic error was modest, and though there may be data flaws in the data in the actual world, they should be rather minor. In conclusion, they found that Integer Linear Programming provides accurate and fast solutions for the sub-team creation issue. In a Binary Integer Programming approach, Ranganathan and Nygard developed a resource-allocation model for a smartgrid. In instances when there is a power deficit, DERs (distributed energy resources) may be distributed to available RUAs (regional utility areas). a capacity-based iterative binary integer linear programming methodology (C-IBILP). The results of all simulations are calculated using the optimization toolbox in MATLAB. When using the capacity-based Iterative Binary Integer Linear Programming (C-IBILP) branch and bound approach, optimum solutions were discovered after 163 iterations with 54 nodes participating in 1.22 seconds. In the previous example, 13 iterations and 0.047 seconds were required when the DERs' preferences were adjusted, resulting in the ideal answer.

2.3 AUTOMATED DECISION MAKING

a decision-making framework for the Air Fleet Refueling Problem was built by Barnes et al. [16] (AFRP). A new paper revealed that the Group Theoretic Tabu Search for the Air Mobility Command (AMC) at Scott Air Force Base is effectively executed (GTTS). With the symmetric group on n letters (Sn), we utilize the Java language to apply it to this issue. To access the missionspecific parameters, the researchers, such as Barnes et al., used the Tabu Search approach, with which they were able to locate some critical parameters, including the number of tankers required, the time of the operation, the distance traveled, the amount of fuel burned in refueling an aircraft, and so on. Sun et al. [17] implemented the Tabu Search heuristic for a Fixed-charge transportation problem in the form of a local search method, incorporating a network-based implementation of the simplex method, and they called it a Fixed-charge transportation problem with network-based implementation of the simplex method. When compared to other models, their model was successful computationally. in this study, the resource allocation issue was analyzed by Belfares et al. [18]. They set out to allocate the necessary resources for a specific plan of action. In order to optimize this issue, the study examined an approach based on Tabu Search and multi-objectives principles that applies progressive resource allocation. This idea followed by the model was to use every resource as much as possible before deciding on another resource. Two different aggregation procedures, the weighted sum and the lexicographic procedures, were assessed relative to the overall strategy. Using the suggested method, the decision-maker will get better answers and more flexibility. According to Vadde et al. [19], an archival facility that passively accepts and collects wasted items from customers as necessary is known as a Product Recovery Facility (PRF). To find the potential models, it was first assumed that PRFs may handle different categories of abandoned goods. A genetic algorithm was applied to tackle the optimization issue using many different criteria. Through the weighted sum technique, the scalar goal function was maximized. The decision maker assumes each criteria is assessed for its total contribution to the goal function. The model discovered how much it would cost to acquire new reusable and recyclable parts as well as how much it would cost to buy used items. When attempting to optimize sales and decrease product recovery costs, the model used competing goals, such as maximizing revenue and minimizing disposal expenses, such as disposal costs, disassembly costs, preparation costs, holding costs, acquisition costs, and sorting costs. Fanti and colleagues [20] developed a scheduling model for flexible production systems. Fuzzy Set theory and genetic algorithms are both used to schedule employees. Each system has several goals, which are in competition with each other, as well as heuristic techniques, which are effective for multi-faceted scheduling, and discrete event simulation-based performance measurements. Fuzzy Logic is used in this work in order to determine production targets as well as for decisionmaking. Unlike information-based optimization algorithms, evolutionary algorithms may find solutions to optimization problems with no knowledge on the decision factors. The results of the numerical trials verify the approach's efficiency. The suggested method of Arroyo and Armentano [21] included elements such as preservation of population dispersion, elitism, and the use of a parallel multi-objective local search to improve search in various areas. A new genetic algorithm approach is devised, which is then contrasted with previous research on branch-and-bound algorithms. The two multi-objective, genetic, local-search algorithms presented in the literature are used to estimate the performance of the method when it's used for up to 80 tasks and 20 machines. Findings computed using the suggested method reveal that the method's results are stable. Zadeh, doing preliminary work in constructing Fuzzy Logic, [22, 23, 24] His research included the introduction of fuzzy sets, which were a continuation of the traditional idea of a set. The membership function in fuzzy sets allows a progressive evaluation of membership of items. As part of the same article, Fuzzy Sets also received an explanation on the many ideas of inclusion, union, intersection, component, relation, convexity, etc. Fuzzy Sets has been used by Zadeh in subsequent work to apply the notion of a fuzzy algorithm. Conversion of relational representation into algebraic form was covered in the essay. Zadeh [24] Delivered a presentation on how Fuzzy algorithms may be used for complicated, poorly specified issues. Even non-disciplinary subjects like music, art, history, philosophy, anthropology, and architecture, among others, may have fields of study known as "problem domains". Rough Set analysis was used in a multi-criteria decision-making study conducted by Greco et al. [25]. To solve multi-criteria decision analysis (MCDA) difficulties, sorting difficulties, and choice or ranking difficulties, they developed a rule-based decision analysis method known as DDX for task assignments. The most notable modification in Rough Set is the replacement of the indiscernibility relation with a dominance relation, which enables approximation of ordered sets when more than one criterion is used. The authors, however, were able to create rules from Rough Set analysis by replacing the data table with a pairwise comparison table, where each row represents a pair of objects specified by binary relations on specified criteria. When it comes to imperfect information systems, Kryszkiewicz et al. (26) devised a strategy. They suggested that information that was not necessary nor helpful for the categorization or decision-making process be removed. The only assumption they made was that “the missing property had a genuine value in the attribute domain.” Decision rules were discovered by computing an incomplete decision table, which yielded rules that could not be fully predictable. Fuzzy and Rough Set theories were mixed to develop a hybrid decision model that used only information-rich input. The model was used for online categorization, and it resulted in an easier classification of websites, while also reducing the number of dimensions without any loss of information. In contrast to the findings of other studies, they discovered that both the hybrid model and the single Rough Set-based model may be utilised in decision making. A company failure prediction study was undertaken by Dimitras et al. [28] using Rough Set. According to the report, a set of guidelines has been discovered that can tell if a business is healthy or failing. They utilized the model to develop rules that apply to 80 Greek financial institutions, and then applied the rules to each of the institutions to calculate their collective health. The two Skowrons, Suraj, and their research team [29] developed a real-time decision-making engine algorithm based on Rough Set. To determine the decision tables' values for conditional qualities, they used sensors to measure those properties. using petri nets, they were able to detect things in the decision tables to a level that allowed them to make good judgments.

3. MATERIALS AND METHODS

The concepts covered in this thesis are summarized in this chapter. After defining power demand and smart-grids, AI Afterwards, we'll talk about the notion of demand management, including the many management approaches and the work done on it throughout the globe in various kinds of electrical networks, with a particular emphasis on smart-network demand management. Last but not least, it focuses on the forecast of electric demand and the numerous strategies used to solve the problem in diverse situations, particularly when it comes to networks with the presence of non-conventional renewable energy sources.

3.1 PROBLEM OF VOLTAGE CONTROL

Power systems depend heavily on voltage management to keep the power flowing. Keeping all nodal voltages within a predetermined working range is the goal of this regulation.

Since it is a multivariable issue in which all nodal voltages might be different, the problem's solution becomes more complicated. Because of the complex interaction between reactive power flow and system voltage profile, the placement of reactive power sources and transmission system structure are both critical to solving the voltage management issue.

Additionally, transmission and transformation components generate and use reactive power in a manner that is dependent on the system's current operating conditions. Transmission and transformation components create and consume reactive power. Reactive power and voltage control may be handled in a variety of ways to keep the grid's voltage profile appropriate and maximize the potential of reactive power sources. To improve voltage and reactive power regulation, a variety of methodologies may be used, including sensitivity analysis [11], heuristic rules [9], expert systems [6–9] and base rules [9].

3.1.1 Voltage Regulation

All of these applications are used to determine the best control methods to implement in order to maintain a constant voltage profile in the system. Voltage variations at producing nodes are used as a control method for steady-state voltage control in this work.

Using a fuzzy logic system (SLD), it is possible to determine the generation voltages that should be changed in order to keep the electrical power system's voltage profile more stable; it is noteworthy that improving the voltage profile in an electrical power system reduces losses due to the transmission of reactive power.

The flow of reactive power in the system must be reduced or eliminated in order to maintain voltage deterioration to an absolute minimum. In real-world systems, the reactive sources are not always proximate to the load demand, necessitating reactive power transmission mechanisms.

During the initial step of voltage control, the system's voltage profile is established by establishing nodes. This voltage control is employed to keep a certain node's voltage constant, and it is thus local in nature. The reactive power injection system, the generator excitation system, and the connections of reactors and capacitors may all be altered indefinitely, as can the way they are connected. An example of how to use local control is presented in Fig. 3.1.

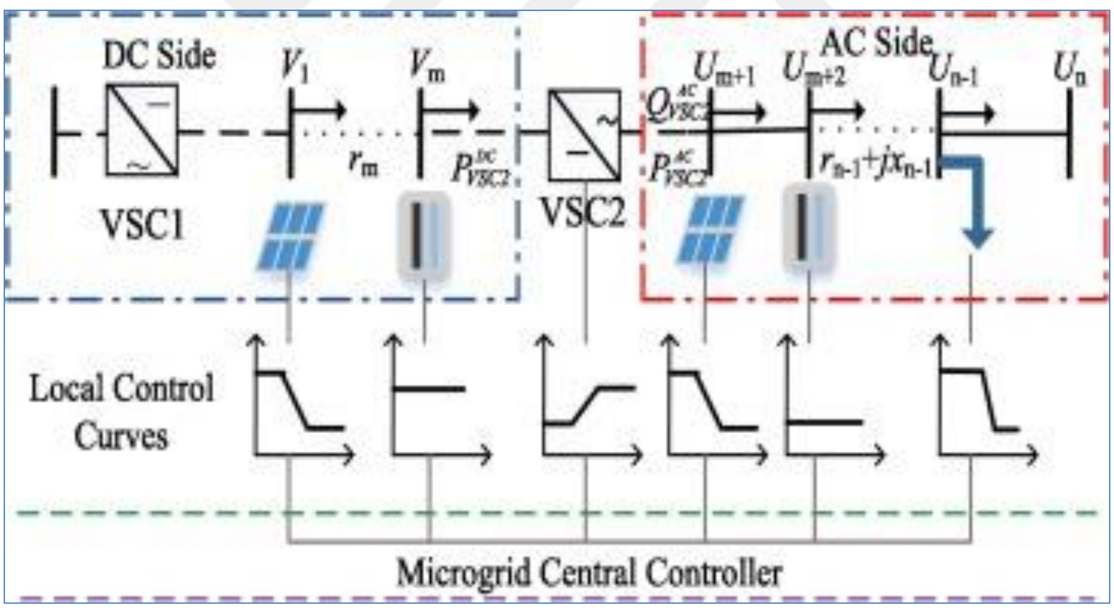


Figure 3. 1: Local Voltage Regulators

3.1.2 AI in Voltage Regulation

voltage providing the reactive power required by the loads and the transmission system. In a real case, the reactive sources are limited and will only be able to maintain the voltage as long as the system's reactive power needs are within the source's capabilities. As soon as a limit is reached, all reagent support and voltage control for that particular section of the system are gone. Reagent sources are critical to the power system's ability to provide enough voltage support and limit the amount of reactive power that is sent to the load nodes. To avoid voltage deterioration due to long-distance transmission of reactants, you must have a large number of reactive power sources and electrically close loads. Because of the higher reagent usage in transmission components due to the larger voltage differential, this is a compounded issue to be aware of.

The regulated node voltage will be maintained constant at the prescribed value in steady state by the controls. To compensate for these fluctuations and restore voltages to their normal levels, voltage-controlled nodes in power systems act as reactive power compensators, supplying reagents as demand dictates in order to maintain a steady level of power in the system. (reference). Modifying the generating voltage has the effect of altering the reaction flow, resulting in a transfer of reactive power between generators and a corresponding change in the system's voltage profile. When it comes to improving the voltage profile, it is important to reduce the flow of chemicals in high impedance channels.

These solutions need a thorough grasp of the issue in order to be developed. Holland (1975) established the fundamental concepts of artificial intelligence, which have been referenced in a number of later writings, including those by Goldberg (1989), Davis (1991), Michalewicz (1992), and Reeves (1993). (1993). The natural drive of an individual to compete with another in a group is to seek for and use scarce resources such as food, water, and safe havens. Even members of a group who are quite similar to one another compete for their peers' attention. Successful individuals who survive and attract wives will have a big number of children to care for and nurture. On the contrary, wealthy individuals are more isolated and have fewer children. As a result, an increasing number of people will be able to pass on the genes of those with the most perfected adaptations to their environment. By combining the best characteristics of numerous forefathers and foremothers, it is possible to generate "superindividual" offspring, culminating in a population that is considerably more adaptable than any of its forefathers and predecessors. When it comes to adapting to their surroundings, evolutionary species exhibit one of the most astounding traits known to man. As a result of the Crusades, new individuals will be created who will share certain features with their forefathers but will also have their own. Reduced adaptation leads in lower reproductive success, implying that less genetic information from an individual is transmitted down across generations. Due to the fact that it has a greater proportion of outstanding characteristics than the prior population, the new population that succeeds the previous one stands out as especially notable. They've been passed down down the years, much like the outstanding features. Cross-pollination of the best-suited persons was my preferred method of searching. A good definition of the issue is critical to the growth of these solutions. It was demonstrated by Holland (1975) that the fundamental ideas of Genetic Algorithms may be found in a number of works,[3] and [4] Individuals in a group have a natural tendency to compete with one another for scarce resources like food, water, and safe havens. Even those who belong to a group that is extremely similar to yours vie for your attention. People who are successful in surviving and attracting other people have a greater chance of having a big family. The opposite is true: those with more resources tend to have fewer offspring. A greater number of people will pass on the genes of those who have evolved the greatest, ensuring that those individuals' traits will be passed down down the generations. It is possible to develop "superindividuals" by combining traits from several ancestors, whose adaptability is greater than any of their predecessors. For the first time in human history, an evolutionary species has achieved one of the finest adaptations to their environment.

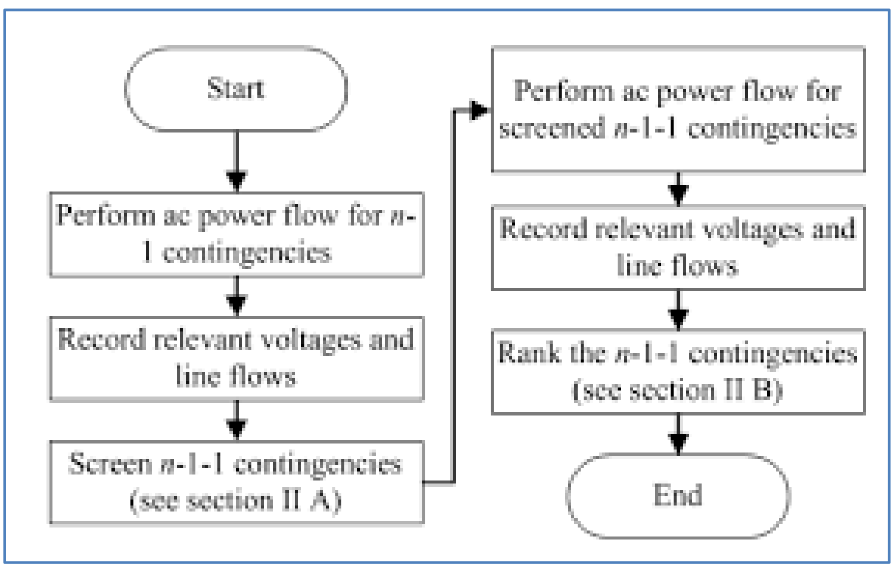


Figure 3. 2: Example of An AI Algorithm for Voltage Regulation

3.2 SMART GRIDS

Distributed generation has gained importance due to the low emissions and low costs it entails. This technology includes gas turbines, fuel cells, and photovoltaic panels. To avoid the problems that these generators can cause, in [1] it is proposed to use these generators and their associated loads as subsystems that can be isolated from the distribution network. These subsystems are called smart networks. Smart-grids correspond to a set of loads and small generators, operating as a single controllable system, that provide energy and / or heating to their associated local area. These may or may not be connected to the main network, being able, in the first case, to isolate themselves against the existence of distribution problems. The energy sources used in this type of network correspond to small generators. the crosses, the carnival and national holidays, the population can reach 500 people [4]. This community is disconnected from the interconnected system of the great north and prior to the installation of the smart grid, the community had a power supply from 2:00 p.m. to 12:00 p.m. from Monday to Friday and from 4:00 p.m. hours until midnight on weekends, obtaining energy from a diesel generator set, whose fuel is provided by the municipality. community has electricity 24 hours a day, thanks to the smart smart-grid installed in the Energy Center of the University of Chile, which is composed of photovoltaic panels, a generator diesel, a wind turbine and a battery bank. In addition, the town has a water pump, which could be used for demand management as a controllable load in future works. The problem associated with non-conventional renewable energy sources is their fluctuation, since they generally depend on weather conditions that vary from minute to minute. This is why the smart-grid generating units must be coordinated, for which in [5] the use of an energy management system (EMS) is proposed that optimizes the operation of a set of generation units and loads, using communication, monitoring and control systems to apply pre-dispatch EMS minimizes smartgrid operating costs in a given T horizon, using discrete time steps that is to say . Thus, the objective function to be minimized is the cost of using the battery bank and affecting its useful life. The EMS problem is solved at a supervisor level at each time step, using unit commitment with a predictive control strategy. A sliding horizon is considered for the control strategy, to reduce the effect of the uncertainty associated with the predictions that are used as input. In smart-grids, to have a safe operation, it is vitally important to maintain the balance between generation and demand. For this reason, one of the topics covered in this thesis is the development of a demand forecasting module for smart-networks, using the smart-network as a case study, to which a stage of analysis of stability so that it maintains an appropriate behavior and is not undefined for specific cases, affecting the system by delivering a failed prediction. For the development of both the community and the smart-network, the social SCADA system implemented in is presented in [6], which is a computational tool capable of relating the electrical and social fields, in order to support the development of community. The indicators that the system presents to the community, so that it can make decisions, are:

A. Monitoring of generation units: This indicator provides information such as the status of the units (on / off) and power injected into the system.

B. Sustainability indicators: This indicator provides information such as diesel savings and emissions.

C. Maintenance management: The maintenance schedule and weekly tasks are delivered.

D. Energy consumption per home: By having the information per home, decisions can be made to support town development in the context of energy saving.

E. Demand response: Provides signals to modify consumption, which will be detailed later.

F. Alarm system: This indicator sends signals when failures occur or are predicted and indicates the action that must be taken to correct the problem.

The energy management system incorporates a demand management system based on demand response, that is, signals are sent to consumers so that they modify their consumption in order to benefit the entire smart-grid. With this demand management system, it is possible to compensate for the fluctuation presented by non-conventional renewable energy sources in order to maintain the balance without the need to increase the use of the generator set.

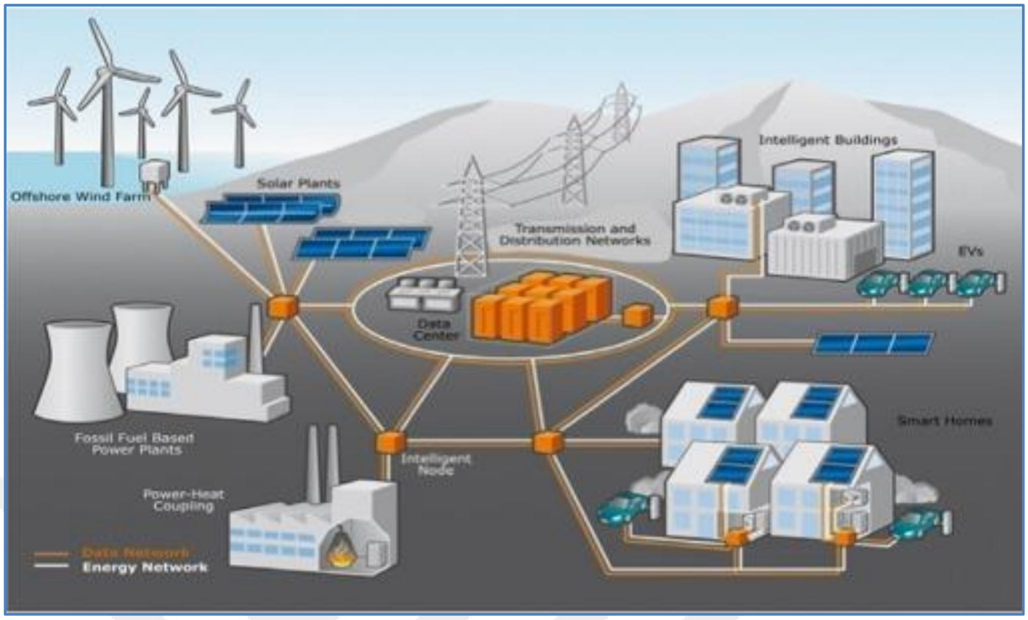


Figure 3. 3: Large Scale Smart Grids

3.3 ENERGY MANAGEMENT SYSTEM EMS

The replacement of conventional energy sources by renewable energy sources has grown upwards in recent years. This assertion is due, in part, to the awareness in favor of protecting the planet, in which the degradation of natural resources is notorious, deterioration generated largely by man himself. Among the proposals created to strengthen the world we live in is “green energy”, energy generated from renewable environmental resources such as sun, wind, low-impact water resources, among others. Green energy storage is one of the current problems, because unlike current energy sources such as hydroelectric and nuclear plants, green energy does not maintain or guarantee continuous production. Solar panels depend on sunlight to generate energy, however, many of the days of a year are rainy, cloudy, reducing the amount of energy generated, the same happens with wind energy, on days when the gusts of winds are low or non-existent. Considering the aspects highlighted above, an intelligent system capable of rationalizing the acquired green energy was designed, in order to design an environment for capturing renewable and environmentally correct energy at an adequate cost/benefit. Energy capture and storage equipment has considerable value, this factor prevents those interested in assembling a structure capable of supporting low energy production for several days at a standard expense. The proposed system uses fuzzy logic to determine the level of economy at which the green system should behave. To accomplish this task, the system searches the internet for weather forecast information associated with the current level of battery packs, this information is processed by inference rules and later establishes the way in which the system operates. To exemplify the argument made, the following situation is put as an axis: Imagine the fact that, under normal conditions of use, that is, without the green energy rationalization system operating, the lights that illuminate a billboard remain on for 12 daily hours, however, there is no weather forecast for the next few days, which favors the exhaustible risk of renewable energy for this purpose, but with the system providing for a low energy production, this lighting would automatically be reduced to fewer daily hours, until the climate becomes more favorable, and thus guarantee sustainability. This article is arranged in five sections in order to clarify the project. After the first introductory section, we move on to the fundamental concepts of fuzzy logic, elucidating the main concepts and exemplifying when necessary. Continuing, the next section describes the ideas and steps adopted in the development of the project. The following section presents the software developed by the author of the article. Finally, section five presents some pertinent considerations.

3.4. FUZZY LOGIC

Lotfi Zadeh, professor of electrical engineering and computer science, developed the theory of fuzzy logic in 1965. Zadeh noted that many of the rules people used to make inferences could not be explained by them. It is in this sense that we refer to this commonly used example: “That man must be 40 years old”, we are not prepared to explain the rules used to arrive at this determination. Based on the ambiguities of thought, Zadeh created fuzzy logic, initially criticized, but ended up being used by engineers and computer scientists Treating subjective and imprecise or even mistaken information is something natural for the human mind, but computers were built and prepared to work with accurate and well-structured information, not being able to recognize information like it's a little hot today, it's almost ready in its initial form. In view of these concepts, fuzzy logic emerged so that this information could be processed it is possible to clearly observe the difference between classical logic and fuzzy logic, classical logic does not make room for intermediate values, while in fuzzy logic it is possible to analyze the intercessory values. A classic example to be given would be: in classical logic the day can be cold or hot while in fuzzy logic there can be several determinations such as: cold, very cold, little cold, warm, hot, very hot, little hot, among others. . For a better understanding of the existing theory in fuzzy logic it is necessary to have knowledge of fuzzy set theory, linguistic variables and inference system. Such definitions are covered in the following topics. Fuzzy sets were developed to determine how much an element belongs or not to a given set, using degrees of membership (□) which are values in the interval [0;1]. Thus, it is possible to determine the elements that belong to a group and their respective degree of pertinence The representation of fuzzy sets depends on the nature and dimensions of the universe to be represented. When it is necessary to represent sets that contain a small universe, the best solution is the analytical one, which aims to present all elements of the universe separated by commas, with each element composed of the degree of relevance and the value of the term. When the universe to be represented contains a large number of elements, it must be represented by the graph of its membership function, called Hassi-Euler diagram (H-E) presents an example of determining fuzzy sets. It is possible to perceive the representation of the universe of elements in item 1 of the figure, being this universe composed of ages. In item 2 of the figure, three sets are created, being young, adult and old. In item 3 of the figure, the degrees of belonging to the groups in relation to the elements of the universe are represented. It is possible to notice that at the age of 30 an individual has a degree of relevance of 0.5 in relation to the young group, 0.4 in relation to the adult and 0.1 in relation to the linguistic variable is the entity used to inaccurately represent a concept or a variable of a given problem. This variable only accepts linguistic values, such as: cold, little cold, very cold, large, very large.

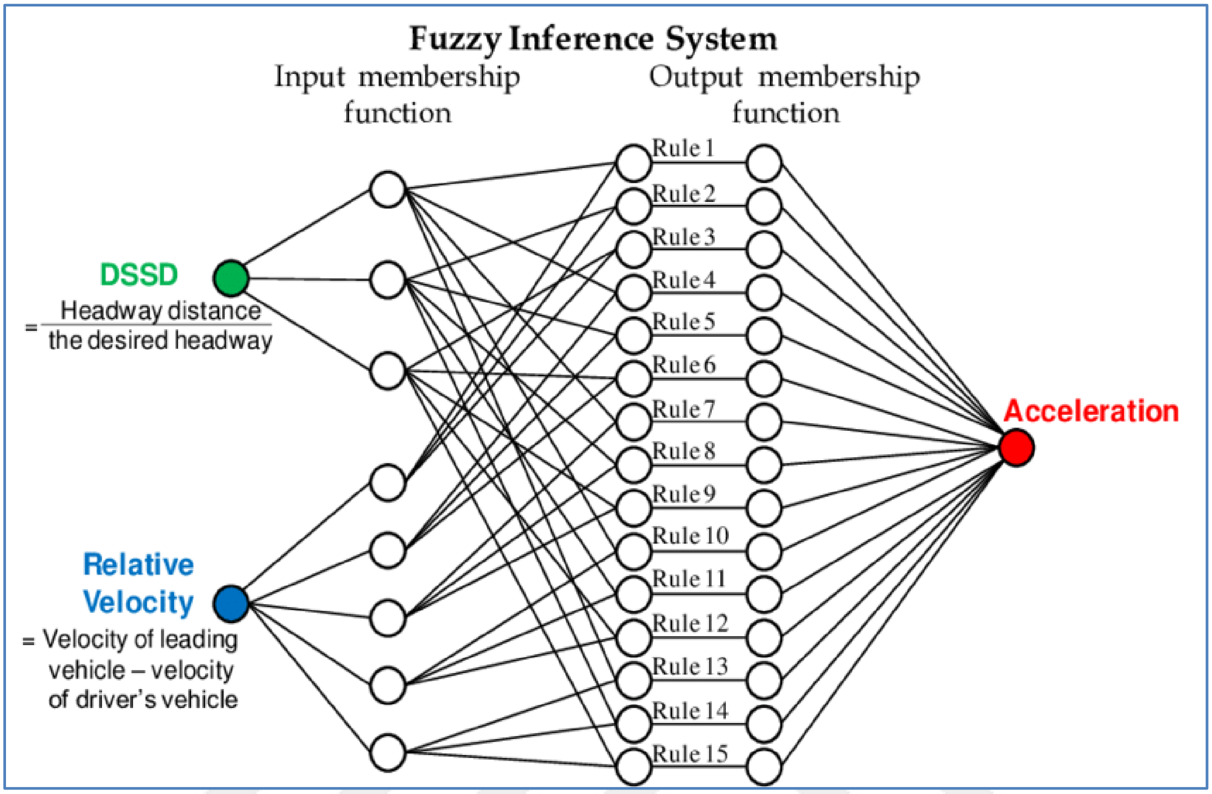


Figure 3. 4: Fuzzy Interference System

Analyzing age can be recognized as the linguistic variable and its values recognized by the fuzzy sets: young, adult and age, these values contrast with old numerical values. The fuzzification process is responsible for signing each fuzzy set the respective membership values. Figure 3 shows an example of the values of possible reference values of membership in the variable speed. Observing Figure 3, it can be noted that the speed of 30 km/h has a relevance of 0.5 both for the value and slow for medium, on the other hand, it can be noticed that the speed of 60 km/h maximum degree of relevance in relation to the average value and null in relation to the slow and fast values The fuzzy inference system or fuzzy controller is composed of three phases, namely: fuzzification, inference and defuzzification. In Figure 4 it is possible to visualize the fuzzy inference system and the form of interconnection between the phases, with each phase having as a principle an input of data, processing on these data and an output. The first step performed in the fuzzy controller is a fuzzification, this process must be performed for each input value and consists of mapping the data to relevant fuzzy sets. Input values are precise values, usually from measurements or observations. The determination process is also responsible for the situation, relevant constraints for a given

In a fuzzy controller, rules play an important role, as the good performance of the system is linked to the production of consistent rules. The knowledge base can be provided by experts through technical terms. This process can be complicated, but, regardless of the expert's knowledge, an alternative for the formation of the numerical returns base is through numerical returns data mining. This method has a good in classification problems The construction of a knowledge base can take place through fuzzy production rules, which is the most common way. A production rule is prepared by two main parts: antecedent, consequent. The structure of a production rule is defined as follows: “If then ”, in Figure 3.5 it is possible to show an example of a production rule, the clause between the if the then is called the antecedent and the sentence after the then is called the consequent The inference phase is responsible for the operation on the sets itself. It determines how the solutions that will be activated and combined and sets are fuzzy output devices The fuzzy inference system most of the time must provide accurate data as output. This is because most applications need this information. The smoking step is responsible for interpreting the information generated by the inference phase. There are several defuzzification methods, among them: maximum, centroid, weighted average, maximum average, center of sum, largest area.

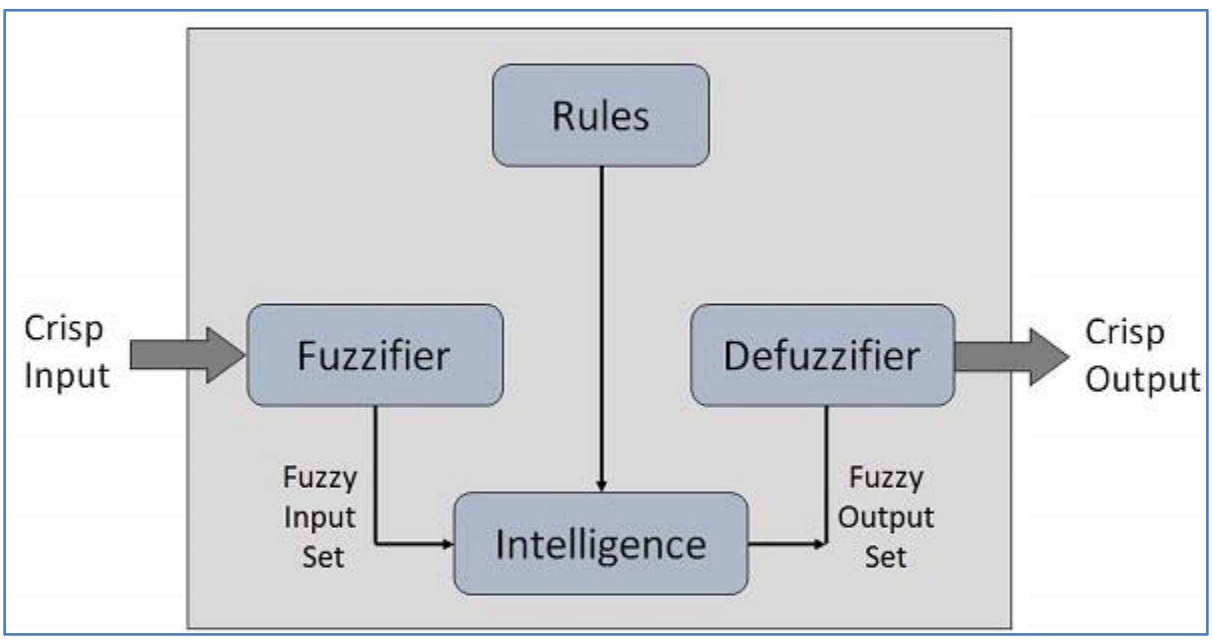


Figure 3. 5: Fuzzification and Defuzzification Stages in Fuzzy Logic

The variable selection phase is based on a method developed by the same authors previously in [38]. This method filters out the variables that are irrelevant and redundant, so that only the variables that contribute to the prediction remain. To choose which variables are irrelevant and redundant, two thresholds are defined: the irrelevance filter threshold "" and the redundancy filter threshold "", which are adjustable parameters. The second component of the lower level is the hybrid prediction engine, which has already filtered variables as input. The prediction engine proposed by the authors, this time in [39], is composed of neural networks and evolutionary algorithms, thus having two adjustable parameters, the number of hidden nodes of the neural network () and the momentum constant of the evolutionary algorithm (). The neural network is assumed to have only one hidden layer. The top level is responsible for optimizing the performance of the load predictor, using enhanced differential evolution (EDE). Differential evolution (DE) is a stochastic search strategy that is based on the current population to guide the search process, developed by Storn and Price [40]. To optimize the performance of the predictor, Amjady and Keynia propose an improved version of the differentiated evolution strategy, obtaining a strategy that has greater convergence and prevents the process of finding the optimum from being trapped in local minima. Uniting the two levels, we have that the individuals of the EDE correspond to the four adjustable parameters of the lower level, that is:,, and. Finally, the validation error of the neural network corresponds to the objective function of the EDE, which is minimized, thus having a two-level structure for the prediction of electric charge. Chan et al [41] used a multiple classifier system, combined with neural networks, to make short-term demand predictions in smart microgrids. The model, shown 17 in Figure 6, consists of four base classifiers. Neural networks are used for these classifiers, since they have a good generalizability. The data used, corresponding to past load information, are divided into four parts: 24 hours, 3 days, 1 week and 1 month before the prediction time. These sets represent the knowledge that is had for different periods of time and diversify the knowledge of the classifier. With these data sets, the four classifiers are trained to later test the prediction of each one and according to their performance, a weight is assigned to each base classifier, which corresponds to the dynamic weight stage. Finally, according to the weights, the information from the classifiers is merged, obtaining a final prediction. The methodology proposed by Chan et al was evaluated using real cargo data from Hong Kong. The factors selected as inputs are: time, dew point temperature, humidity, pressure at sea level, wind speed and whether it is a weekday or weekend.

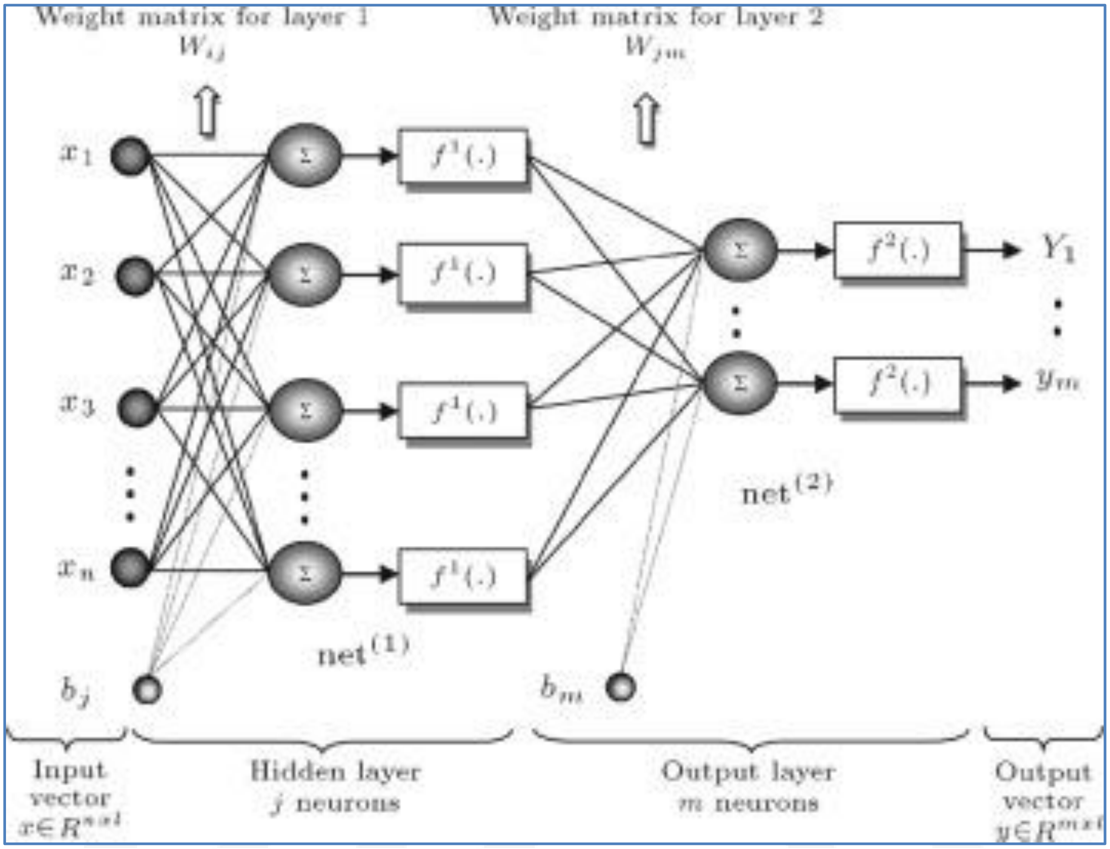


Figure 3. 6: Fuzzy-NN Structure

This method is compared with the use of Wavelets Neural Network (WNN) to perform demand prediction, using the MAPE index as a means of comparison. As a result, it is obtained that the proposed prediction methodology has a MAPE lower by 1.01% than that obtained when using WNN Demand prediction is an important factor in the management of electrical systems, since it allows correct scheduling of unit dispatch in the short term and helps in planning investments in generation and distribution when it is used in the long term. For this reason, there are various techniques for forecasting demand. In microgrids based on renewable energies, having a correct demand prediction is even more critical, since any change in the use of electricity can have a significant impact on the operation of the microgrid, and must also be considered the fluctuating behavior of renewable energy sources. For this specific case, the techniques used consist of several stages, within which neural networks are generally included, due to the non-linear behavior of the demand. Another technique used to maintain the balance between generation and demand is demand management, which also serves to avoid demand peaks and reduce the use of polluting energy sources by making better use of renewable resources, through changes made in the demand side.

3.5 DISTRIBUTED MANAGEMENT SYSTEM

The concept of demand management (DSM: Demand Side Management) was introduced in 1980 by the Electric Power Research Institute and was defined as a series of activities carried out by the government and public companies to increase social benefit and decrease the need to invest in the electrical industry [42].

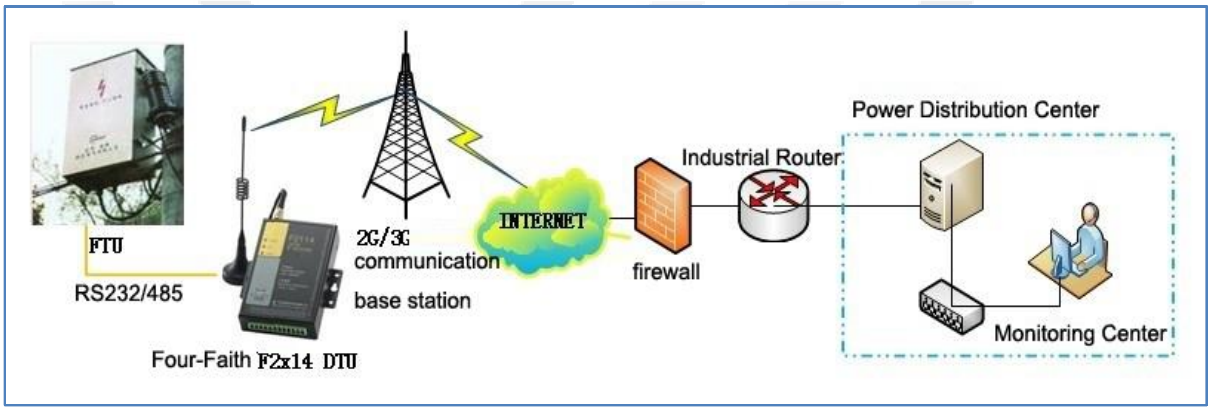


Figure 3. 7: Demand Side Management DSM [12]

The main objective of DSM's programs is to increase energy efficiency on the demand side, which benefits both consumers and generators. A smart DSM should aspire to make an effective interaction between the network and the user to improve service and support access to green energy. In general, DSM programs are designed, as shown in the graph in Figure 3.7, for [43]:

A. Reduce demand peaks: This is applicable when there are capacity problems for short periods of time, such as on a hot afternoon where multiple air conditioning machines are turned on or on cold mornings where industries are turning on the machinery and they also need heating at the same time.

B. Filling in the valleys of the demand curve: This is used in long periods where demand is notoriously lower than generation, so resources are being lost.

C. Achieve a strategic load increase: This applies when there is a large excess of unused generation capacity.

D. Move cargo: When there are peak demand problems on a regular basis and customer loads can move within the day, such as changing production patterns in the industry.

E. Make Load Flexible: The use of energy with high fluctuation rates, such as that coming from wind turbines or photovoltaic panels, results in thermal plants being affected by changes in loads more frequently, this can be counteracted by making loads more flexible in intermittent generation function.

F. Interaction between the network and users.

G. Improve energy efficiency.

H. Provide comprehensive information.

I. Information on electrical equipment must be available for design.

J. It must be useful to solve environmental problems (emission reduction).

The following sections present demand management techniques, first for electrical systems in general, detailing the main techniques used to implement these programs. Then, demand management techniques applied specifically to micro-grids based on renewable energies and the results obtained in various countries are specified.

4. PROPOSED METHOD

4.1 FUZZY LOGIC- ARTIFICIAL NEURAL NETWORK ANFIS

Logic is a subject of study of reasoning methods. A reasoning method means that to create a new proposition from the present proposition. In classical logic, if a proposition is p, it must be either true or false, so the truth-value of the proposition is 1 or 0. For more than a century two-valued classical logic dominated the world. However, this traditional two-valued logic brings many problems along and there were failures at its truth-values. Fuzzy logic part is designated as a transition to the absolute truth and proposes a value in the range of the binary system which classical logic tells. This generalization provides the reasoning performance by giving fuzzy propositions namely uncertain results in classical logic, variables have to be one of the values such as; cold-hot, zero-one and young-old. At the beginning of the 1920s, came up with the idea that is the opposite of this classical logic. In fact, by saying that classical logic can have the intermediate values, he laid the foundations of many-valued logic. Max Planck in 1937 by publishing an article on Philosophy of Science journal, he has drawn the first fuzzy set curves via applying object sets to this valued logic. The first idea of fuzzy logic is put forth by Lotfi Zadeh in 1965 with his Fuzzy Sets article. However, in the Western World of the time, these ideas were approached with suspicion and got huge responses. In the last 30 years, classical logic gave its place to the logic known as “fuzzy” and started to being used in technological devices. In here verbal expressions from daily speaking language are added to the process while modeling with microelectronics, the latest developments in the area of the sensor and wireless communication technology provided a new network structure; wireless sensor devices run on batteries. The self-configured structure called wireless sensor network consists of little devices equipped by individual sensors and a wireless receiver. The primary purpose of a wireless sensor network is to collect the data from the environment and send the observed data to an analyzable reporting site. Wireless sensor devices at the same time can also answer the queries sent by a control site. Finally, under certain conditions, wireless sensor devices can be equipped by actuators for mobility. These networks are sometimes specifically called wireless sensor and actuator networks.

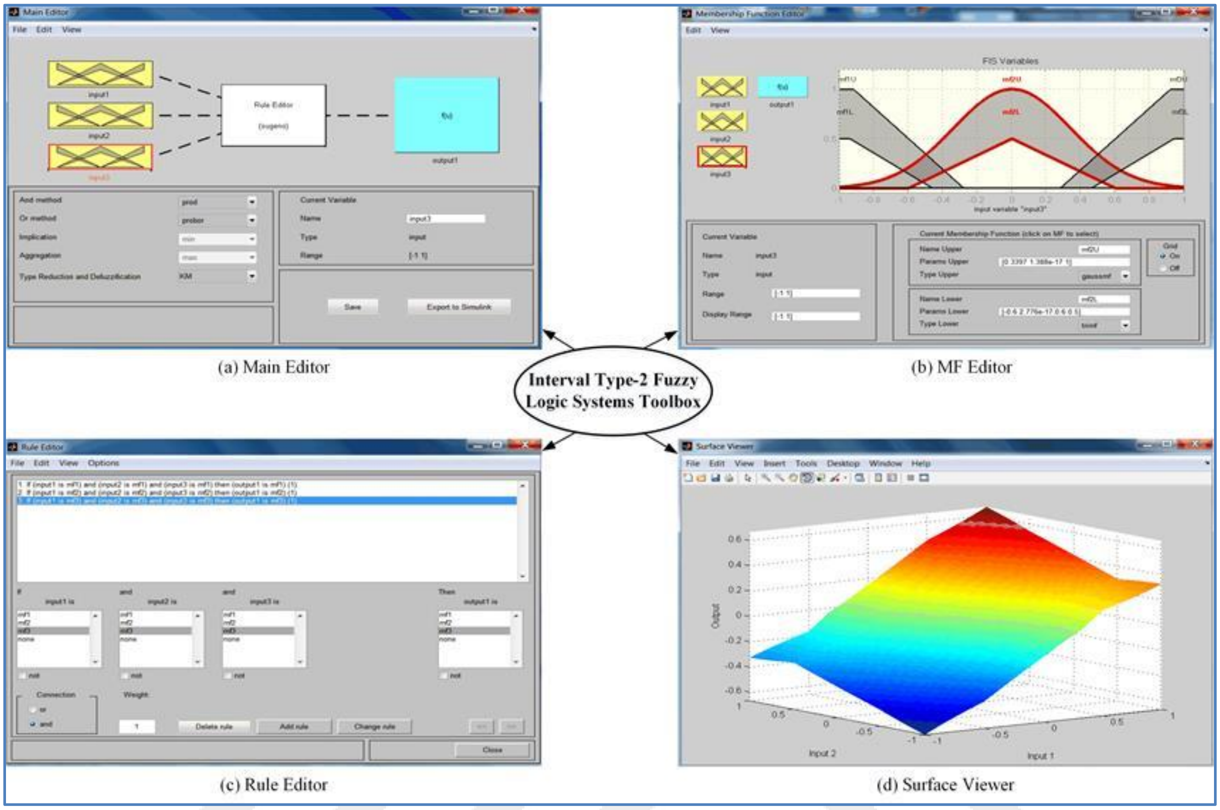


Figure 4. 1: 4D Fuzzy Logic Toolbox in MATLAB

Due to economic and technological reasons, nowadays power skills, memory and communication quality of wireless sensor devices are restricted. Because of that in the wireless sensor technology, efficient algorithms and protocol designing about energy and necessary calculations are focused. At the same time, because it is used at simple data focused on observing and reporting tasks, its application area is so restricted. On the other hand, wireless sensor networks, which can do more than this, are developed. More improved functions and multimedia data transfer feature is added. With new network architectures, in heterogenic devices and expected improvements in the technology, eliminates these restrictions. Thus, the application spectrum for wireless sensor networks is being developed significantly (M.A. Labrador and P.M. Wightman, 2009). Distributed control system architectures consist of different units in the field. These units can be wireless sensor nodes, smart sensors, velocity control devices, network gateways, and computers. An example of a distributed control system architecture is shown

According to the classical set theory, there are only three members $\boldsymbol{x1}$, $\boldsymbol{x2}$, $\boldsymbol{x3}$ in the set B under the age of 40, because of this, the border is so wide between over 40 years old and under 40 years old faculty members. In Figure 5 this border can be seen clearly. However, for the fuzzy set theory, the set B does not only contain these three members s $x1$, $x2$, $x3$ but it also contains other members in changing degrees. Distribution of ten teaching staff's real age on the x-axis is shown in Figure ٤.٢. When this graph is examined, it can be seen that s $x4$ and $x5$ are not the members of the set B, but respectively with their rates of 0.7 and 0.3 membership degrees, they can be considered as partial members

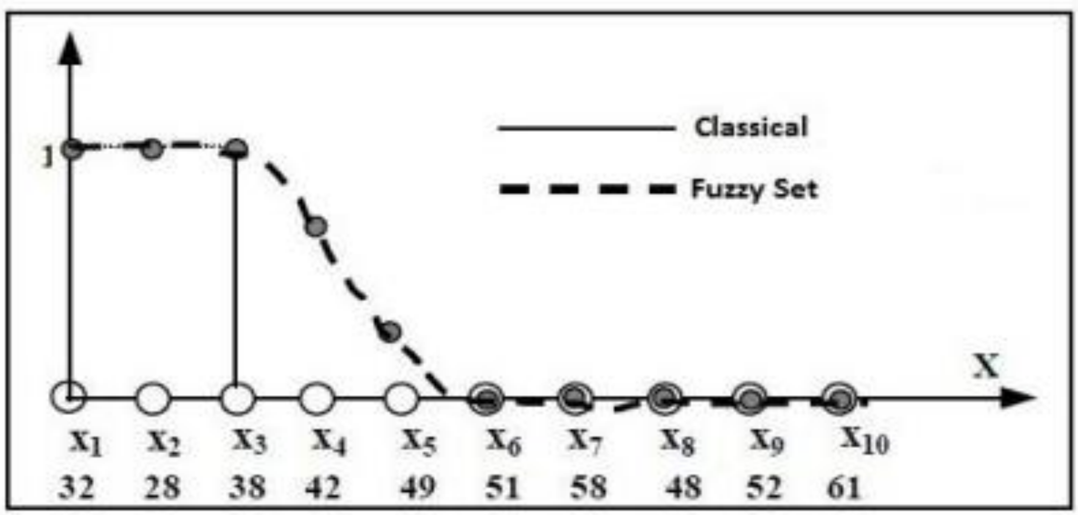


Figure 4. 2: Fuzzy Set Decile Over Rules

When it comes to a distributed control system's design, there are two distinct types of members: the master and the slave. Slave units include, but are not limited to, wireless sensors, velocity control devices, and proportional valves. They are only responsible for data collection and transmission to the superstructure's central node. Nobody or nothing has the authority to hold them responsible. computers, and visual control units are just a few examples of master units. The master unit's role, as implied by its name, is to provide command and coordination. It is feasible to monitor the whole system from a single location due to the utilization of slave stations. The hierarchy of masters and slaves is shown in Figure 4.2. To sustain this master-slave relationship, a communication protocol must be implemented. There will be no cables needed with this method, and only one cable will be necessary to maintain system control. Additionally, this way of communication improves the security of the information. There is a hierarchical order in a distributed control system and this system’s function units are placed distributed. In these infrastructures, there are powerful and autonomous automation systems. Domain points or control loops (1) are restricted by the measuring point. The infrastructures, which are functionally autonomous and placed in this area, are called field stations. The first task of the field station is:

A. To do the preliminary check by collecting analog and digital signals.

B. Transmission of the tracking and the field messages.

C. To do the open and closed-loop control processes.

Every server has two backed up a server in the condition of not exceeding one or two keys. At the same time, all control systems are connected to the link server. These keys help to the communication between the client and the controller. Distributed control systems can operate one or more than one workstation and can be configured by a personal computer at the workplace. Extra computers, which have the abilities of data collecting and reporting, can be added to a server and/or applications. In typical distributed control systems, there are regulatory control cycles that have the executive ability between 1-256 and distributed to a geographical area.

Mamdani type fuzzy inference gives an output that is a fuzzy set. Sugeno-type inference gives an output that is either constant or a linear (weighted) mathematical expression, thus using Sugeno will add computational redundancy as the ANN will already compute weights to the inputs.

4.2 FACTORY SYSTEM DESIGN

The main structure of the designed system called stations. At the beginning of these stations, there are conveyor belts carrying products. At the stations generally, the packaging process is done by operators and the products stands in front of them are put into their places. There is a energy source to carry the products to the logistics department in the factory. In our designed system there are three stations. At every station, there are laser distance sensors thought about to check products' fullness ratio. In the system, there is a wireless sensor network structure, and fullness ratio information is transmitted via wireless nodes. At the same time, to check the energy sources if they are coming to the right station, there are SMART GRID read/write tags exist on energy sources. Automatic and manual working modes are aforethought together in the system. Manual mode is developed to intervene in case of a breakdown. In automatic mode, the system works by itself until the factory is entirely stopped. When the factory is opened, operators set the system to automatic mod and system stays active for the whole day.

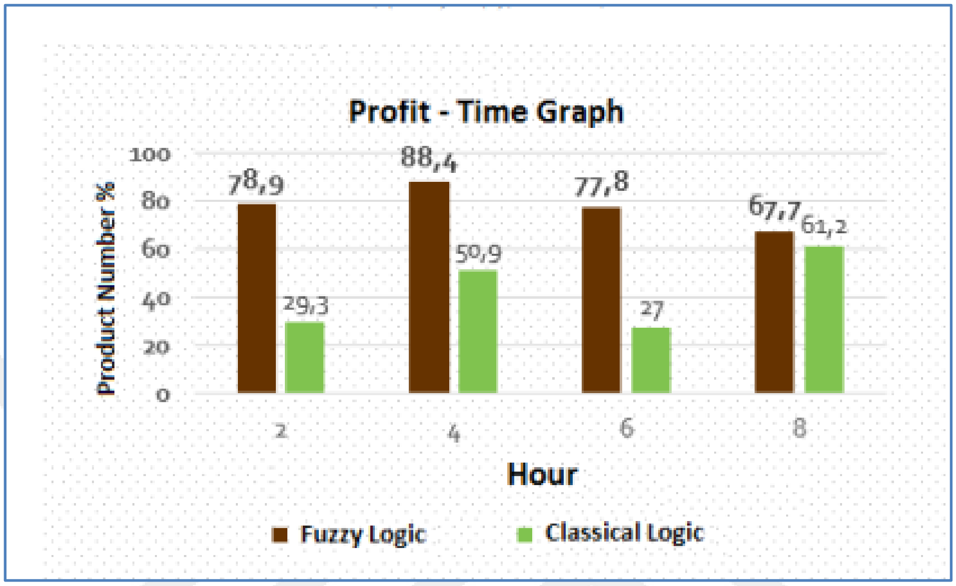


Figure 4. 3: Time Graph Comparing Fuzzy Logic and Classic Logic

4.3 ALGORITHM FOR THE DESIGNED SYSTEM

first of all, a control algorithm is designed. This control algorithm will be explained part by part. The first control algorithm is created to decide according to the fullness ratio of the products at the stations. At every station, there are laser distance sensors to observe the fullness ratio. From the operator panel, according to daily working conditions, a limit fullness ratio will be entered. For example, on the 1st day, if a quick product shipment is wanted, the limit of fullness ratio should be entered lower. If there is no such priority, a normal limit value may be entered. It must be decided only according to working conditions. Another possibility is that at every station there are different products are produced. In such a case, some products may be maybe desirable in more copious amounts depending on days. The limit value entered from the operator panel can solve this problem too. All algorithms are created for one station, and the control of all stations are same Energy sources perform the necessary tasks by steering to the station where the information comes. However, in case of a mishap or when the operator perceives the following information wrong, they can be misdirected. To prevent these, some other technologies can be applied. The most up-to-date method for such applications is SMART GRID technology. This technology can read and write with radio frequency and has its unique tags. In these tags, there are specific memories. For example, if a name wanted to be written in it, its memory should be more significant. However, if only a number wanted, a regular size of memory can be chosen. There are reading/writing nobs to do the reading and writing processes. These are divided into two according to their detection distance such as HF (high frequency) and UHF (ultra-high frequency). E.g., at the entrances of highways, there are UFH technology is being used. In order to adapt to our application, tags are attached to every station, and there are two reading/writing nobs on energy sources. At the installation phase, a code is given to every tag at stations, and they are stored. In the PLC program when a energy source goes to the wrong station, operators must be warned.

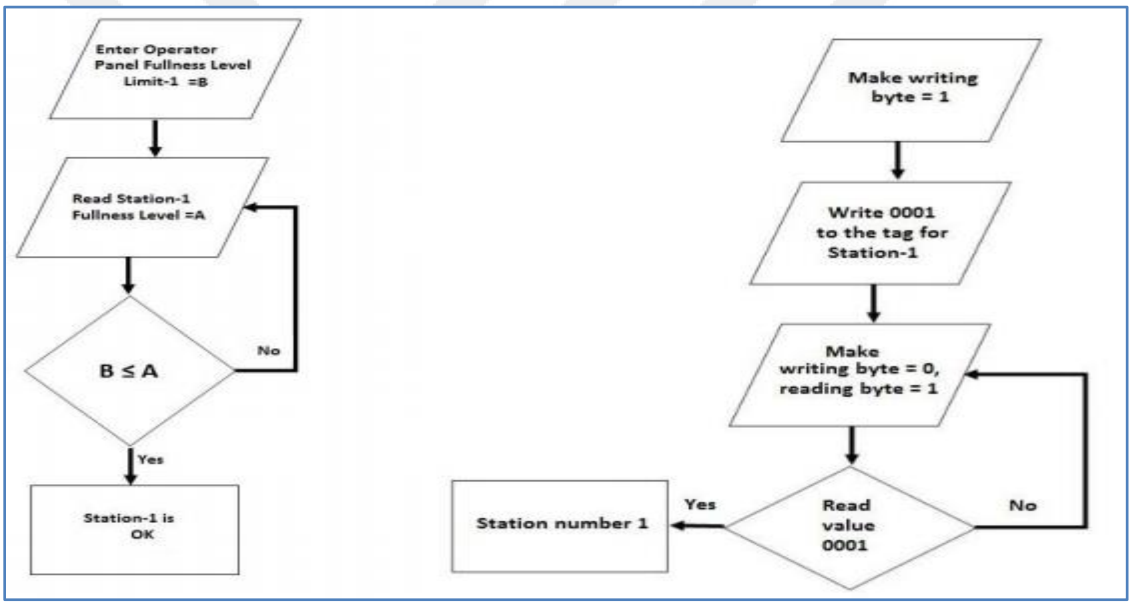


Figure 4. 4: Fuzzy Logic in Programmable Logic Interface

Fullness control of station. Analog 4-20 mA signal corresponds to the numerical value 0-32767 in the PLC program. This value's type is the word in PLC. Firstly it should be converted into REAL type. Expressing the values in decimal value is critical. After that, by using simple mathematical operations, this value is converted. As can be seen in Figure 16, the value ‘istaston_1_lazer_sensör' is coming 20000 from the field, and when this value put on the formula the real measuring value is found 610 mm. This value, which is in REAL data type, can be used in every POU. The use of SMART GRID technology is mentioned in the algorithm part. Detailing the subject, in SMART GRID tags there are memories to write some values. By activating specific letter can be written how much of these memories can be used. These bytes are called ‘byte count,' and there are 3 of them. If ‘1' is written in these 3 bytes, all of the memory becomes available. In SMART GRID structure, choosing reading or writing processes is related to the bytes to be activated. There are two bytes for reading and writing. Firstly, writing byte is activated and codes are written in the tags. After writing the codes, with the codes read in the program, and at the stations, true-false control is made. at the section number one, the activation of writing byte is seen. When the reading byte is activated in the same way, the writing byte is deactivated automatically significant bytes to activate are shown to use the memory part. Analog signal processing, activation of the reading/writing nob with the help of the sensing unit exists in the energy source, is illustrated. At the fourth section, a value is written for the code to be given to the particular station. At the fifth section, it is shown how to read from the tags codes written in it. At the sixth section, a comparison made between the read and present values and a result about stations truth is obtained.

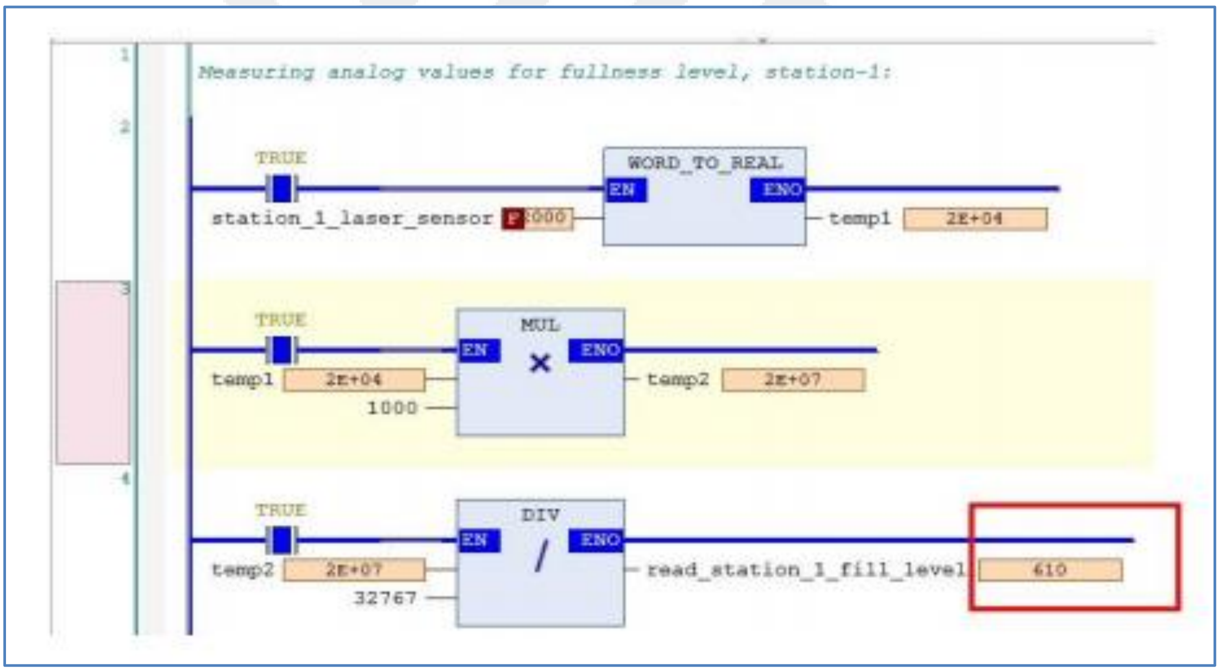


Figure 4. 5: Fuzzy Control System

4.4 CONTROL OF THE SYSTEM WITH FUZZY LOGIC

In a factory system, energy sources carry the products with manual control logic. To make it clear, at two of the stations when the products are ready, energy source operators are going to the station the first one they see or without any priority. This manual control logic causes inefficiency and energy loss at systems. In order to prevent this situation, a fuzzy logic approach is tried for this manual control. A decision-making mechanism algorithm is developed for the energy sources to choose a station which one to go and take the product. When the movements of the energy sources are considered, taking the products from the stations without any delays is a critical expectation. To meet this expectation, parameters about the energy source movement, which creates the fuzzy logic model, become very important, inputs and outputs of the fuzzy logic are illustrated. Input and output parameters of the system the most successful directing with fuzzy logic model belongs to the energy source movement, according to finishing ratio of the products and the distance between energy sources and the station, is aimed.

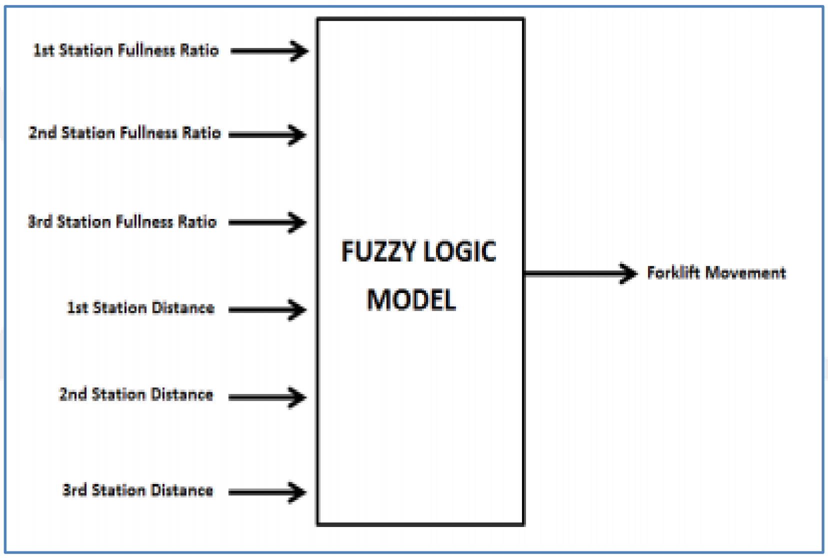


Figure 4. 6: Example of Fuzzy Input Rules in An Energy Source System

By using the output of the sensor, the parameters are obtained during the movement of the energy source. As an input to the system, determination of the fullness ratio at the stations is given. As another input, 6 inputs are determined by obtaining the distance between the energy sources and the stations. With this information, movement of the energy source is decided. Energy source's movement is assigned as one input in the system. While designing the system and creating the fuzzy logic block diagram, a suitable software program is used. The fuzzy logic control, which its rules were created, is evaluated by two different methods. These methods are called Mamdani and Mamdani method needs supervisor information, it is commonly used and can be used at every problem-solving. Sugano is used in the applications with fewer variables. At the same time, fuzzification and defuzzification processes can be done in the software program. In Figure 20, a screenshot of the designed page is given. As it can be seen on the editor's page six inputs and one output is defined. Besides, Mamdani method is used and named as "Energy source application 1". The next step is creating membership functions in input and output functions. The software editor, which is used, lets us choose the type of the function. The most used type is a triangle type, and this type is used in this application. Fig.20.

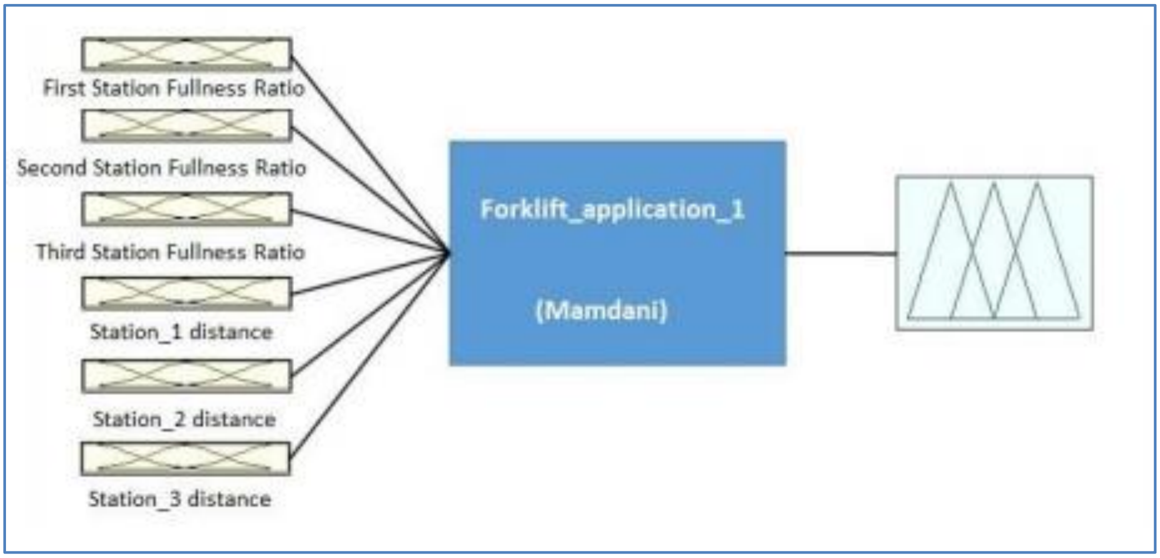


Figure 4. 7: Applying Fuzzy Set to The Previous Example

Fuzzy logic editor for the fullness ratio of the stations defined as an input, three membership functions are assigned. Membership functions are divided into three parts such as low, medium, high. This input value is given in percentage. Membership functions of this input are given in These membership functions are the same for these three stations. Membership functions belonging to station fullness ratio Three membership functions are defined for the energy source's movement, defined as the output. Membership functions are divided into three parts as energy source's movement station1, station2, and station3. These output values are defined between 0 and

4.5 MATHEMATICAL MODELLING OF THE FL

In this regard, we use the fuzzy logic to determine the level of power voltage demand and generation and the need to switch between power demand and power generation from one bus to another or from one source to another, the figure 3.31 below shows proposed fuzzy decision-making scheme while the figure 3.32 the switched we use to turn on an off a power source or a faulty load:

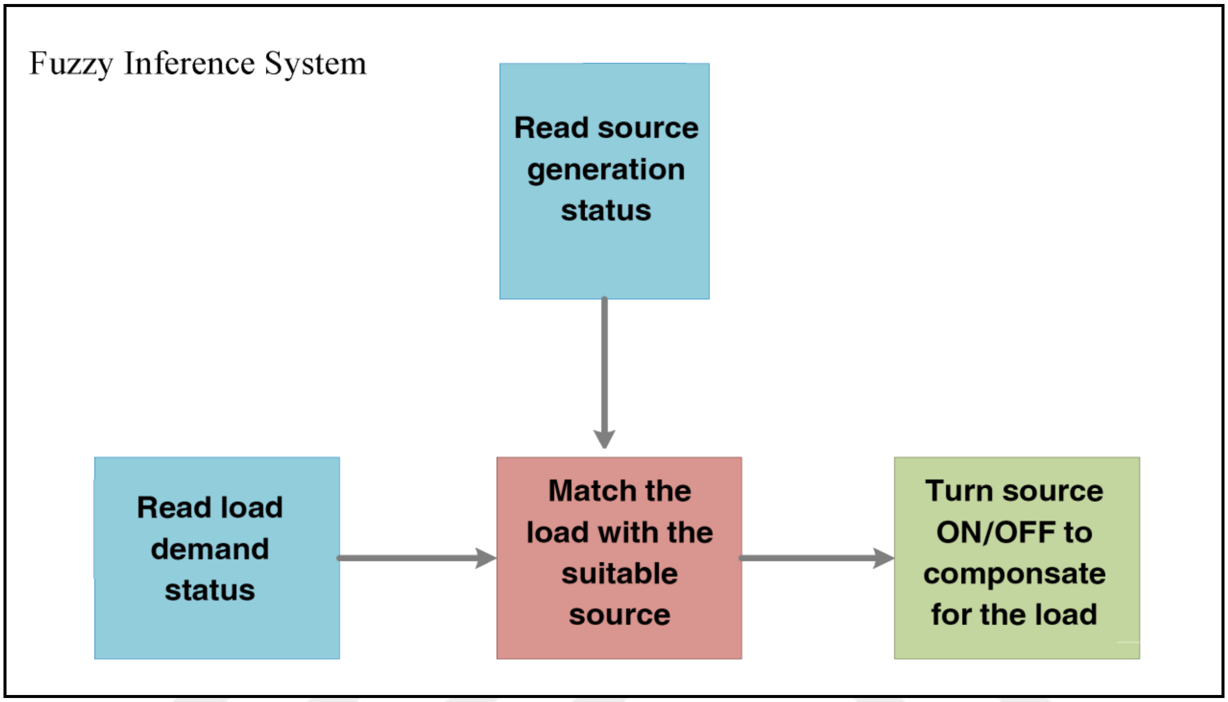


Figure 4. 8: Proposed Fuzzy Rule Control Scheme

We simulate the grid connected assets mainly, loads and sources and use them as input arguments of the fuzzy logic controller to make the decision of turning ON or OFF a source when a failure or an over demand occurs the figure below shows the control of these assets by the fuzzy logic module inside MATLAB:

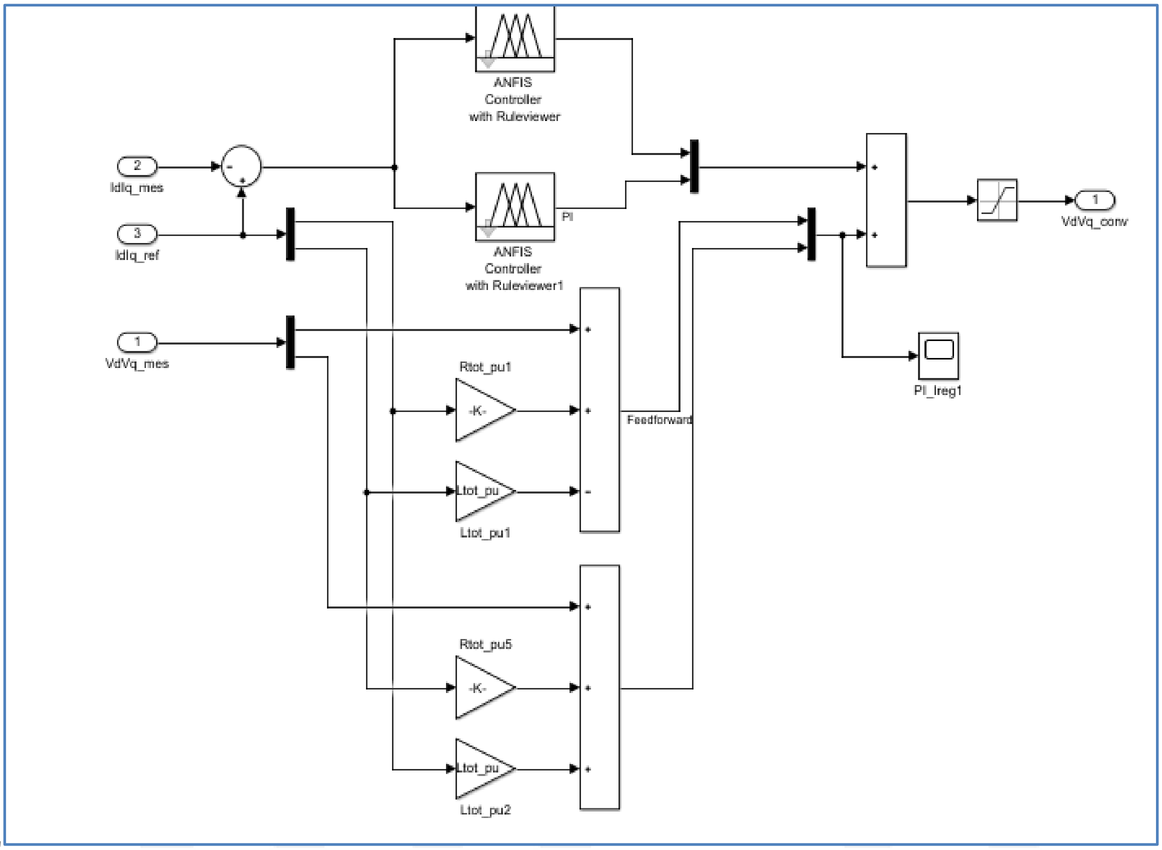
E 

Figure 4. 9: Shows the MATLAB Implementation of The Fuzzy Logic Controller

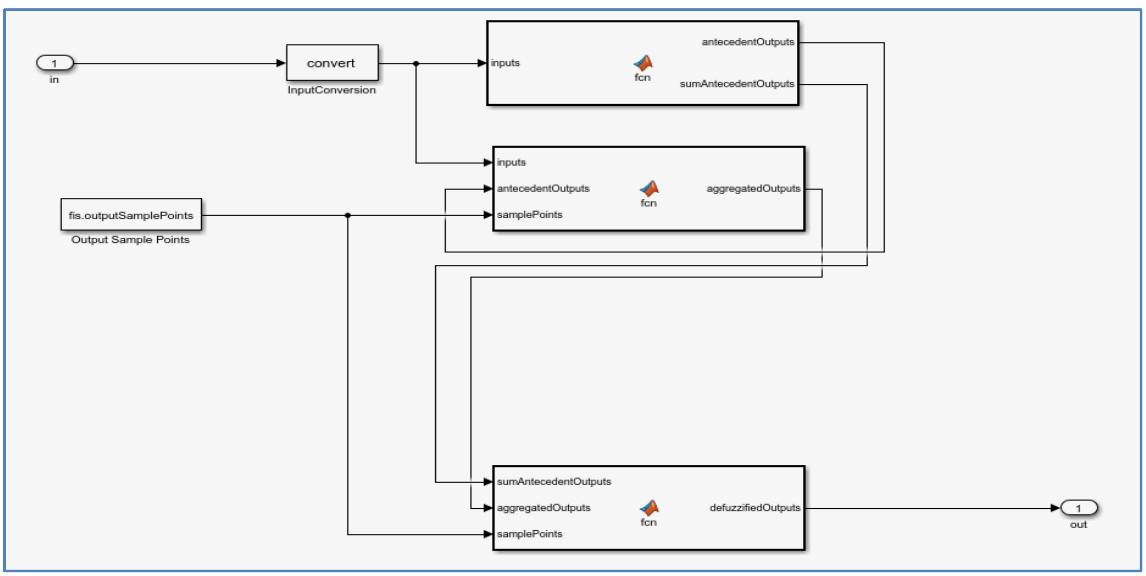


Figure 4. 10: Fuzzy Logic Controller Module in MATLAB

4.5.1 Fuzzy Rules

Membership functions of the output variable Membership functions belonging to energy source's movement in order to create the model, after creating the membership function, 12 rules are created to determine the necessary interactions between parameters. These rules are created according to the supervisor's information, and the scenarios can happen in the field are considered.

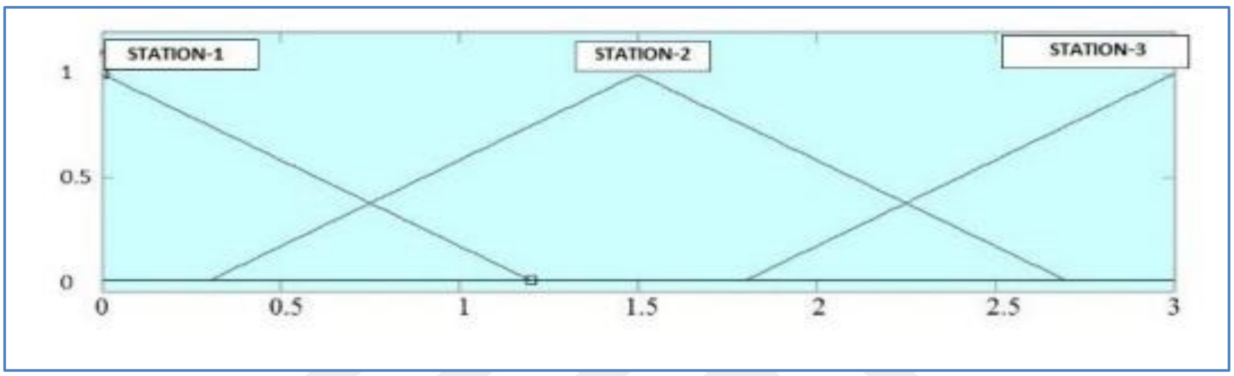


Figure 4. 11: Mamdani Fuzzy Set Solution

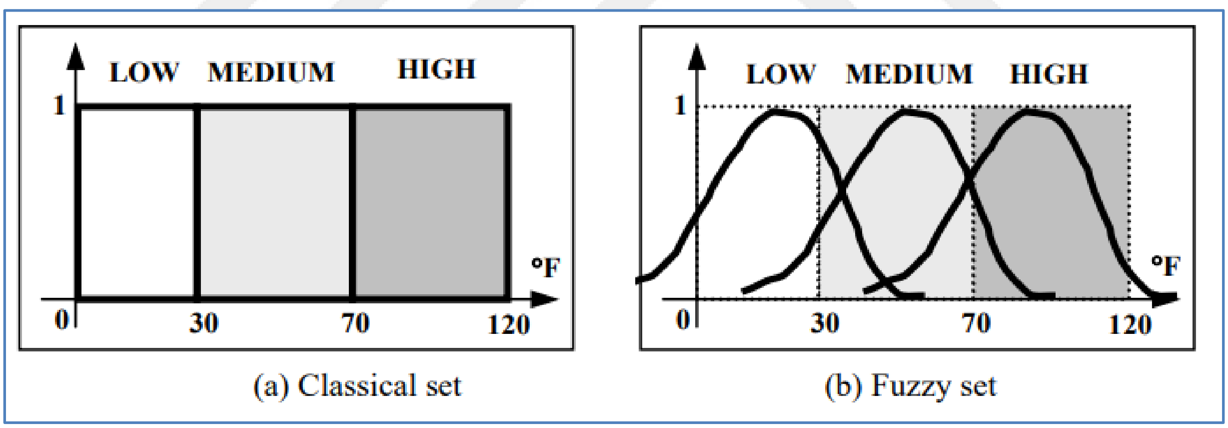


Figure 4. 12: Difference Between Fuzzy and Classic Values Where the X-Axis Is the Rule From (0-1) And the Y Axis Is the Degree of Change

The fuzzy rules used for calculating the inputs and outputs and to achieve stability in the system are denoted by the anachronyms below:

Table 4. 1: Fuzzy rules in the proposed system where d is decrease in demand (low demand) and i is increase in demand (high demand) and n is neutral (standard demand)

Rule	Station1	Station2	Station3	=	PV	Fossil
R1	N	N	N	=	ON	OFF
R2	I	N	N	=	ON	ON
R3	I	I	N	=	ON	ON
R4	I	I	I	=	ON	I
R5	D	I	I	=	ON	I
R6	D	D	I	=	ON	I
R7	D	D	D	=	ON	ON
R8	D	N	N	=	ON	ON
R9	D	D	N	=	ON	I
R10	D	N	D	=	ON	OFF
R11	N	D	D	=	ON	OFF
R12	N	N	I	=	ON	I
R13	I	N	D	=	ON	ON
R14	D	I	D	=	ON	ON
R15	D	N	I	=	ON	I
R16	N	I	I	=	ON	I

Table 4. 1: Fuzzy rules in the proposed system where d is decrease in demand (low demand) and i is increase in demand (high demand) and n is neutral (standard demand) “tables continued”

Rule	Station1	Station2	Station3	=	PV	Fossil
R17	D	I	I	=	ON	OFF
R18	I	D	D	=	ON	ON
R19	N	N	I	=	ON	I
R20	D	I	N	=	ON	ON
R21	I	D	I	=	ON	ON
R22	D	I	N	=	ON	ON
R23	I	I	D	=	ON	ON
R24	I	I	N	=	ON	I

For example, these rules can be summarized like:

A. If the fullness ratio of the first station is high and the fullness ratio of the second station is low, and the fullness ratio of the third station is high, and the distance to the first station is short and the distance to the second station is far, and the distance to the third station is far, energy source goes to the first station.
B. If the fullness ratio of the first station is low and the fullness ratio of the second station is high, and the fullness ratio of the third station is low, and the distance to the first station is far and the distance to the second station is short and the distance to the third station is far; energy source goes to the second station.
C. If the fullness ratio of the first station is low and the fullness ratio of the second station is low, and the fullness ratio of the third station is high, and the distance to the first station is far and the distance to the second station is far and the distance to the third station is short; energy source goes to the third station.

D. If the fullness ratio of the first station is high and the fullness ratio of the second station is high, and the fullness ratio of the third station is medium, and the distance to the first station is medium and the distance to the second station is medium and the distance to the third station is medium; energy source goes to the first station.
E. If the fullness ratio of the first station is high and the fullness ratio of the second station is high, and the fullness ratio of the third station is low, and the distance to the first station is short and the distance to the second station is far and the distance to the third station is medium; energy source goes to the first station.

4.5.2 Fuzzy Rules Visualization

As a result of these fuzzy rules, rule visualizer is shown in Figure 4.13. Rule visualizer includes the entire program until the rules are made. The part number one, so the yellow graphs in the first six columns of the figure show the membership functions belong to the rule entries. Blue graphs in the seventh column show the membership functions dependent on the result values of output. The blue graph right below the third part shows how every output became integrated and defuzzification. When pressed on the entries by making some changes on the entries, a change on integrated output value (the red line) is observed. In this way, rule visualizer gives the opportunity of explication about the changes and fuzzy systems. The information received from the rule visualizer is explicated according to the information below.

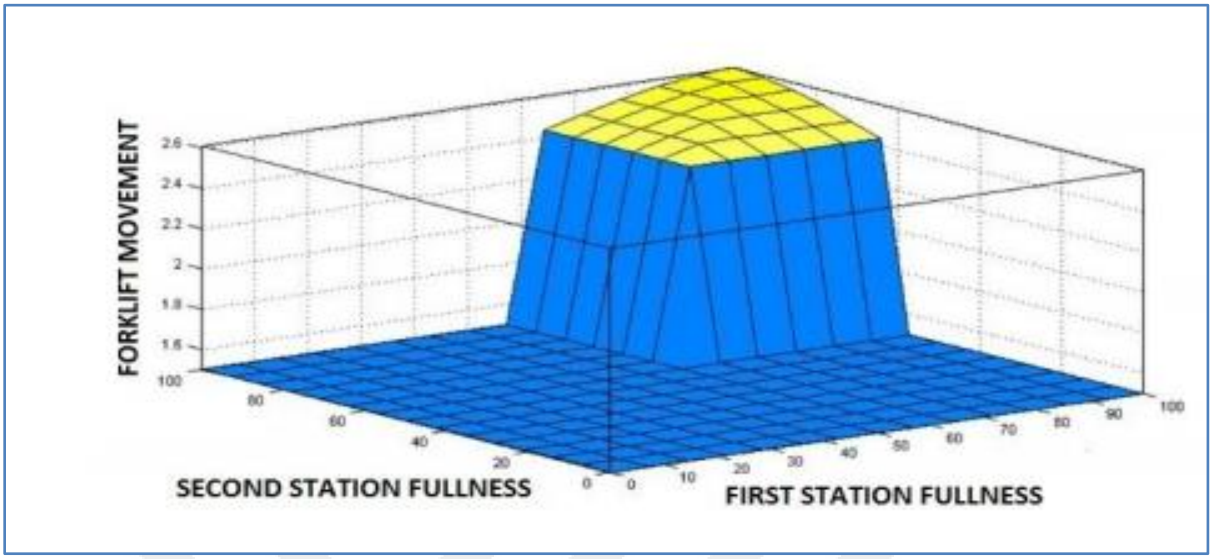


Figure 4. 13: Fuzzy Normalization of The Input Data Where the X-Axis Is the Movement Position and the Y-Axis Is The Probability of Fullness

5. SIMULATION AND RESULTS

The image of the final population through the vector of objective functions $F(\vec{P})$ is called the Pareto frontier. An example of a Pareto frontier can be seen in figure 8; the abscissa axis corresponds to economic costs and the ordinate axis corresponds to the amount of emissions. All points on the boundary represent non-dominated solutions, so it is not trivial to distinguish which solution is better than another. Therefore, higher-level considerations are required, through the decision maker DM, to choose a solution. For each of the 24:

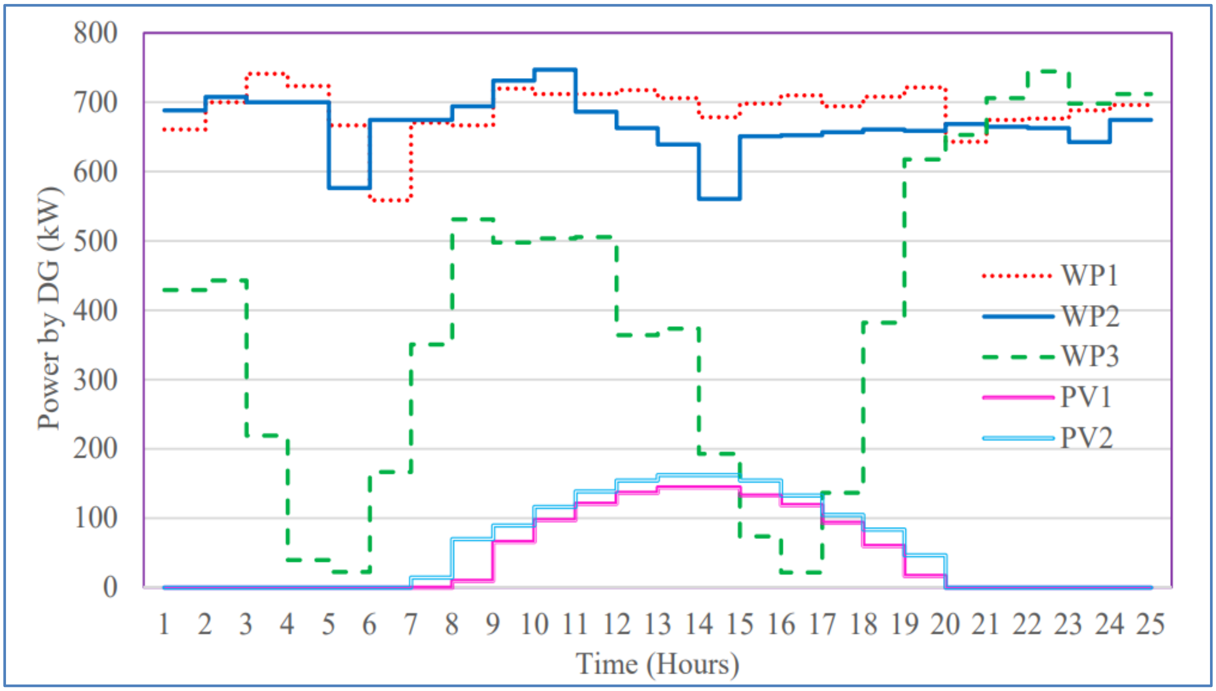


Figure 5. 1: Electrical Load Profile PL And Power in AEDG Technologies Evaluated Over 24 Hours Where the X-Axis Is the DG Power In KW And the Y Axis Is The Hours of Runtime

hours of operation of the microgrid, a set of solutions was generated like the one in the figure

Table 5. 1: Electricity consumption compared to hourly use

Hour	Load (kW)	Electricity Price ($/kWh)
1	1471	0.043
2	1325	0.035
3	1263	0.026
4	1229	0.022
5	1229	0.022
6	1321	0.038
7	1509	0.043
8	1663	0.07
9	1657	0.28
10	1643	0.744
11	1643	0.744
12	1652	0.744
13	1666	0.28
14	1639	0.744
15	1642	0.372
16	1640	0.363
17	1676	0.112
18	1920	0.077
19	2214	0.065
20	2382	0.079
21	2382	0.235
22	2327	0.1
23	2174	0.056
24	1903	0.048

Pareto frontier example of the FUZZY LOGIC optimization algorithm obtained in a microgrid, operating with connection to the main network Population = 100, Iterations = 400

Given that the microgrid can interact with the main electrical network, making exchanges of the electrical resource, this section makes a comparison of economic costs and environmental emissions between the management strategy carried out by FUZZY LOGIC and a strategy for the total importation of energy, where there is no contribution from DER generators. The results of economic costs obtained under the FUZZY LOGIC strategy, including the DM, are compared with the costs generated by the total import strategy; This comparison is observed

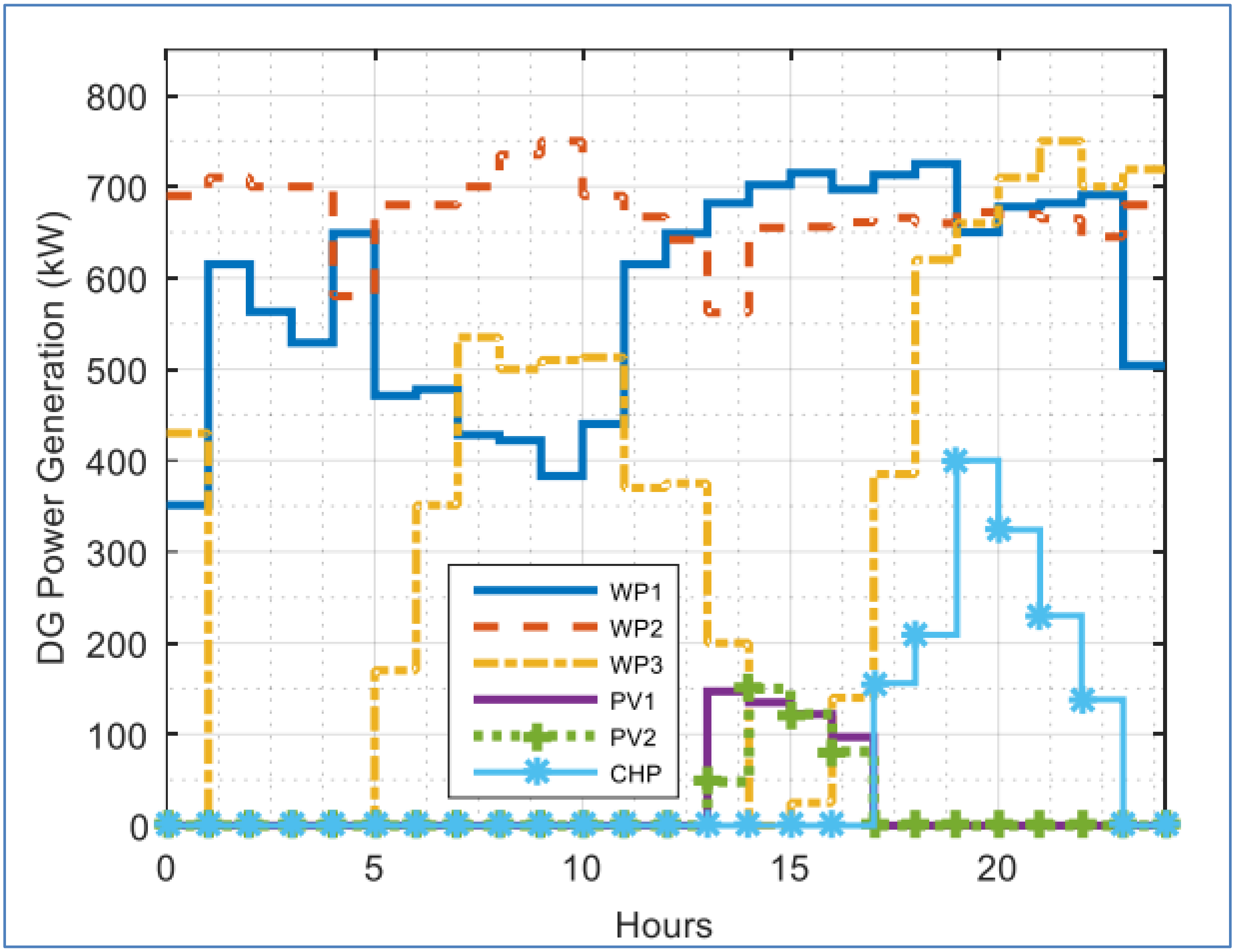


Figure 5. 2: Optimized Electricity Consumption n 20 Hrs Where the X-Axis is The DG Power In KW and the Y Axis Is the Hours of Runtime

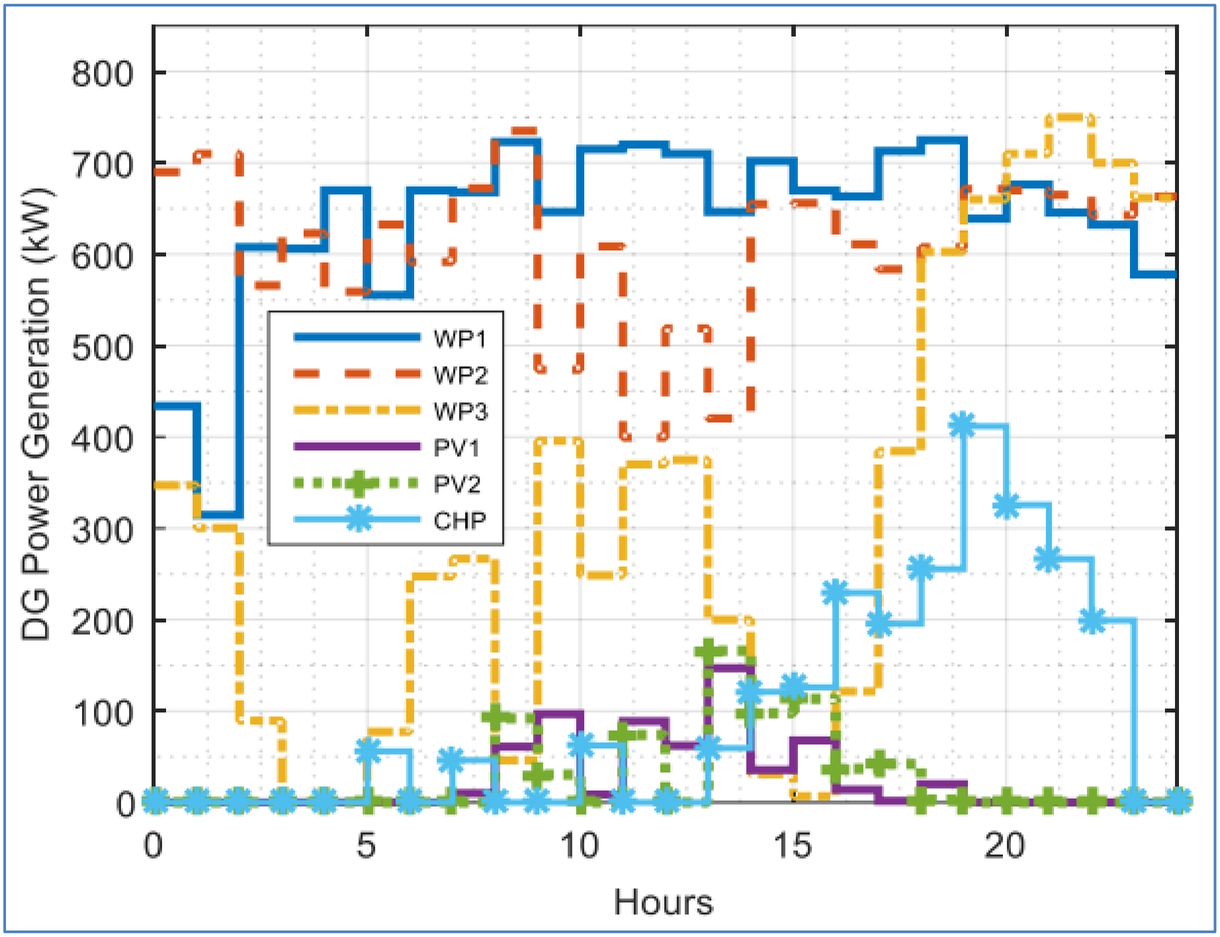


Figure 5. 3: Optimized Electricity Consumption in Another 20 Hrs Where the X-Axis Is the DG Power In KW and the Y Axis Is the Hours of Runtime

note how there is a significant cost reduction when implementing the fuzzy logic strategy. compared to the total import strategy, this reduction in percentage terms is 51.7%, for the 24 hours of operation the reduction in the amount of polluting gas emissions between the total import strategy and the fuzzy logic strategy is quite noticeable, as can be seen in figure here, the emission curve of the import strategy shows a fairly high trend in the peak hours, where the relationship between demand and emissions exhibits exponential behavior.

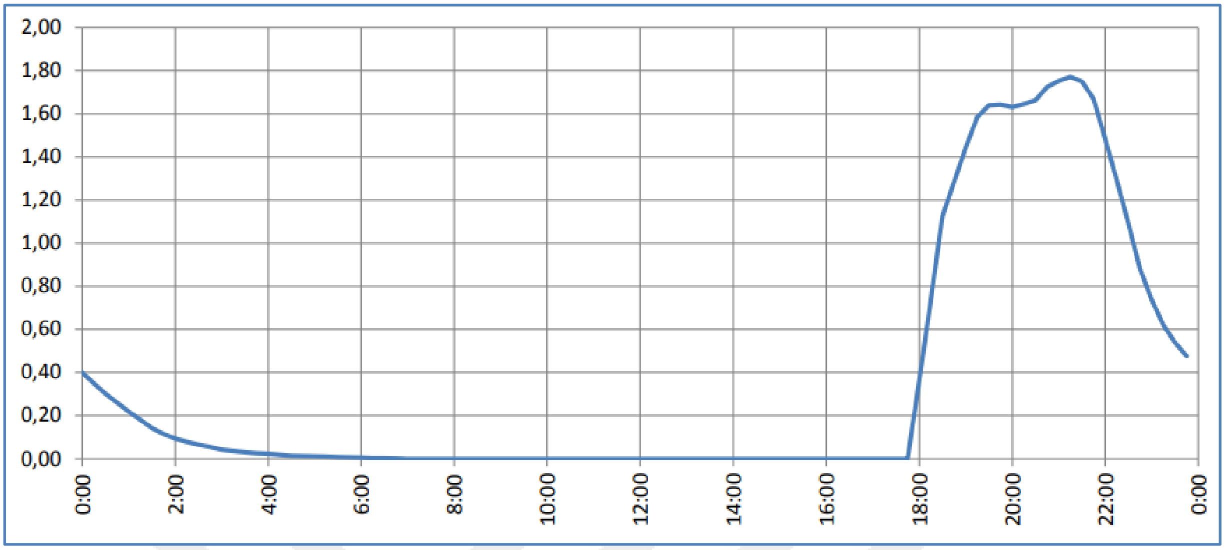


Figure 5. 4: Energy Optimization Using Fuzzy Logic Where the X-Axis Is the Energy Consumption in GW And the Y-Axis is the Time of the Day For 24 Hrs

The energy participation graph shown in the bar diagram of figure above shows how the FUZZY LOGIC optimization strategy offers a trend towards the use of the least polluting and cheaper DER technologies - this is the case of the microturbines (MT01 and MT02) and fuel cells (FC01, FC02 and FC03) -, while reducing the participation of the most polluting technologies such as diesel (DG01 and DG02) and biodiesel (BG01, BG02 and BG03). In addition, the DS system has been charged almost four times to its maximum capacity (as indicated by the negative sign) during the 24 hours of operation.

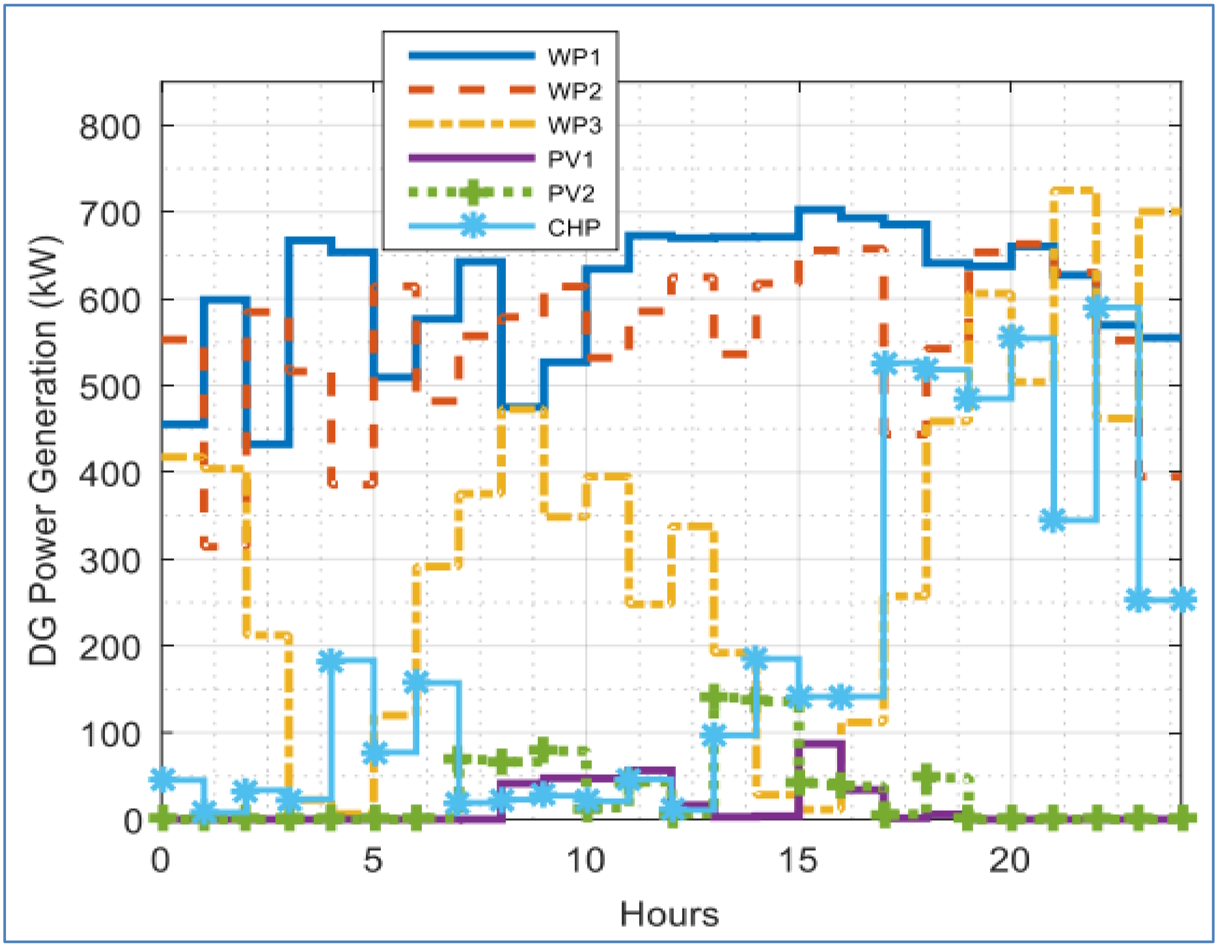


Figure 5. 5: Optimized Electricity Consumption In 20 Hrs Using Fuzzy Logic Where the X-Axis Is the DG Power In KW and the Y Axis Is the Hours of Runtime

To forecast future demand, a growth projection of the base scenario has been made with the growth data of the CNEL Guayaquil concession area. This approach has been taken due to the lack of higher quality information on the specific growth of the area. The specific growth of the area by types of consumers has been calculated, obtaining 0.19% for residential consumers and 0.93% for commercial consumers. On the other hand, an expansive growth of 9.77% was obtained derived from the value obtained for the concession area, and considering that the growth of the pilot area will decrease over time due to the saturation of the buildable space:

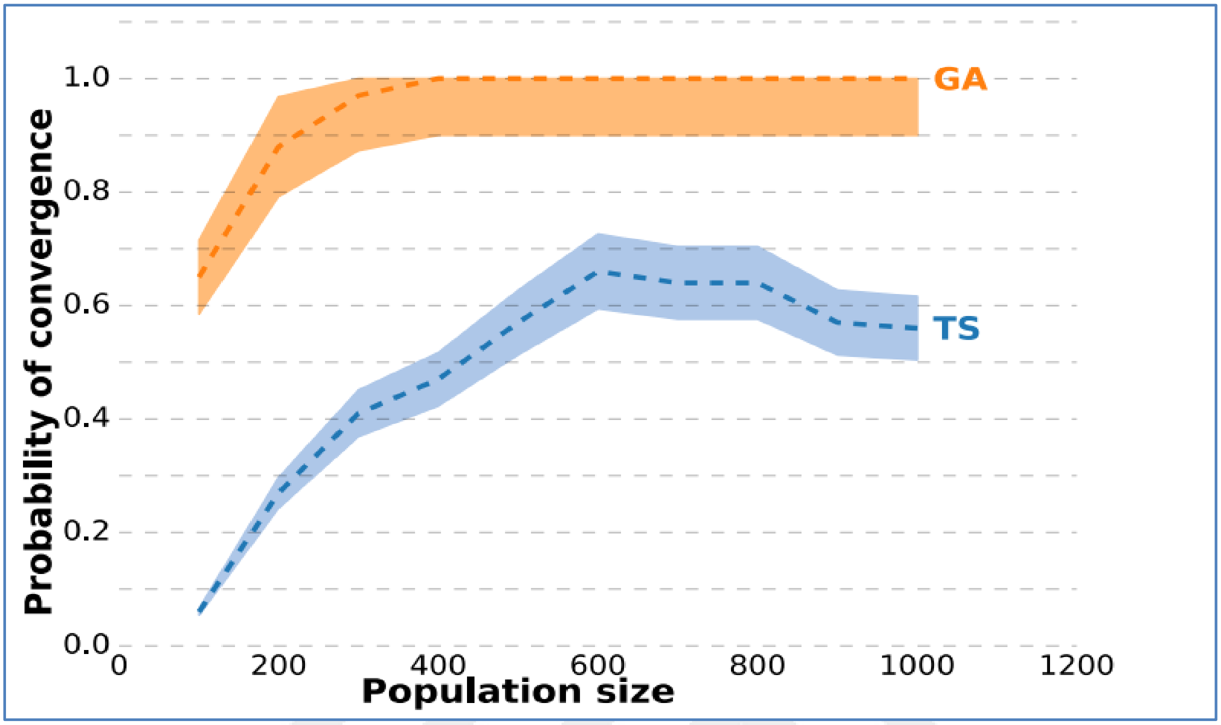


Figure 5. 6: Fuzzy Logic Accuracy Where the X-Axis is the Probability of Convergence, and the Y Axis is the Population Size

Numerous scenarios must be tested, including one in which all loads get power and all sources work smoothly, and another in which either the source or the load demand has faults and mistakes, or both. The image below illustrates the stability of voltage flow in each of the above-mentioned buses. Due to the large amount of energy created, the first stage's stability is very volatile, as seen in the image below.

When a power source fails, resulting in a loss of voltage stability or power generation, the fuzzy logic control reacts quickly to compensate by increasing power from a solar PV array battery; the voltage flow in the fossil fuel generator bus decreases in the first yellow line, while the voltage flow in the battery bus increases in the middle yellow line, as illustrated in the figure. When a power source fails, resulting in a loss of voltage stability or power production, the fuzzy logic control rapidly increases power from the remaining sources. The battery bus is stable.

6. DISCUSSION, CONCLUSION AND FUTURE WORK

6.1 RESULT DISCUSSION

There are various demand management techniques, which have the common objective of increasing energy efficiency from the demand side. The most widely used techniques correspond to load control and demand response. In the first, the loads are directly intervened, with whose owners an agreement has been reached previously, on the other hand, the demand response techniques correspond to mainly economic incentive programs to modify electricity consumption. It is relevant in the networks to maintain the balance between generation and demand, this becomes difficult when dealing with micro-networks based on renewable energies, where the energy sources present fluctuations. This is why various works were presented that support the use of demand management actions in micro-grids that use renewable energies as a means to cushion the fluctuations present in non-conventional renewable energy sources, bringing as a benefit a reduction in costs. of energy, by giving dispatch preference to renewables, compared to energy sources that operate with diesel or gas. Also, to maintain the balance between demand and generation in micro-grids, especially based on renewable energies, it is important to have a good prediction of electricity demand, since this allows a correct programming of the dispatch of the generating units in the short term and also long-term investment planning in generation and distribution. This thesis work was developed on the two topics treated in the state of the art; demand management and demand prediction, based on the smart micro-grid installed in Huatacondo. A model was made to predict electricity demand in micro-grids, using the micro-grid installed there as a case study, which due to the non-linear characteristics of its demand led to the use of fuzzy modelling by Takagi and Sugeno [7]. The variables used were the records of the day before at the time that we want to predict, this was decided based on the correlation study carried out in [9]. The fuzzy model used finds the parameters of the consequences using the least squares criterion for each rule. The number of rules was chosen by carrying out tests for different numbers of rules, choosing the one that presented the best performance, this defined as the lowest RMSE, thus resulting in four models as candidates. A new stage was added to the identification of the model, the stability analysis, which is based on the study of the stability of the state matrices and the stability of the matrices that result from multiplying them crosswise. From this new stage it was obtained that of the four candidate models, the only stable one turned out to be the one built with 4 rulers. Subsequently, 192-step predictions were made, corresponding to two days, with different data sets and the model chosen from the previous stage, observing that the error does not necessarily increase when using data sets far from the training set, which It may be because they are similar in consumption. When comparing the results obtained with those of the neural network model implemented in [8] for three-time horizons (1 hour, 1 day and 2 days), comparing the RMSE of both models, it was possible to see a clear advantage when using fuzzy models for the three horizons studied. It was concluded that the fuzzy model improved the predictions by up to 14% using the sliding horizon technique. This result is important for EMS, since programming can be done with more accurate data. A test was also performed in which the model was trained frequently between 7 and 30 days with different amounts of data, to analyse the appropriate frequency of training. From the above, it was obtained that the incidence of training frequency is not noticeable in the error rate. Relevant changes are expected if the model is trained every 3 months coinciding with the seasonal changes, for which data from at least one full year are needed. In addition, it is obtained that training with more data improves predictions, so the amount of training data should be increased to make the model more accurate. The predictions were tested in the demand management system optimizer, comparing with a simulation that used previously made predictions, which correspond to adding random noise to real historical demand data. The new prediction, made with the fuzzy model of Takagi and Sugano, presented an error 11% lower than that presented by the previous prediction, with respect to the real demand data. This improvement was reflected in costs, which decreased by 15% in the two-day optimization. The second topic dealt with corresponds to demand management of the micro-grid installed in Autacoid, which corresponds to the type of "demand response", which consists of sending signals to consumers to modify their electricity consumption so that the dispatch of the units are optimal, thus reducing costs.

6.2 CONCLUSION

Within demand management, the work of this thesis focuses on two specific aspects. The first is the load displacement factor, which is determined by the energy management system optimizer, which is finally transformed into the signal that consumers see in their homes and corresponds to how much the load must be displaced to have an optimal dispatch. The second is related to how the demand management signals, seen by consumers in their homes, affect the prediction of demand based on their behaviour. The displacement factor is bounded by the load displacement range. In this work, it was proposed to determine this range dynamically using fuzzy intervals. Takagi and Sugano fuzzy modelling was used to model the interval, and two methodologies were also proposed to predict the interval at j steps, since the optimizer uses two-day predictions. When modelling the range of displacement with fuzzy intervals, historical data of demand variation are being taken into account, and it is for this reason that the model is used since the displacement factor will thus be within historical variations of demand. This was tested in the energy management system optimizer, using two intervals with different confidence levels. One of the intervals has a confidence level of 60% and the second 97%, the first being narrower. The upper range was calculated as the variation between the upper bound of the interval and the demand forecast, the lower range was calculated analogously using the lower bound. These two intervals were compared with the case without demand management, that is, where there is no displacement factor. The test resulted in that the greater the displacement range, the lower the final costs, this was expected since increasing the range provides more flexibility to the optimizer to displace the demand. This will not necessarily happen in reality, since consumers do not see how much their demand has to vary, they only see the signal to increase (green) or decrease (red), so the demand will not shift exactly as the displacement factor Indicates it. Therefore, it is concluded that it is not necessary to use high ranges of displacement, which is analogous to wider intervals, since high displacement factors that have a low probability of being fulfilled by consumers would result. The second aspect addressed, in relation to demand management, corresponds to how the demand prediction is modified based on the demand management signals received by consumers. To model the variation in the prediction, the use of Mamdani fuzzy modelling was proposed. The proposed model has as inputs the time and the colour of the lights, while the output corresponds to the variation in the demand forecast. The rules of the model were obtained in a heuristic way, by applying surveys to 17 houses in Autacoid, in which it was asked at what times certain electrical appliances were used (from 7:00 a.m. to 12:00 p.m.), in order to four cases. The first case corresponds to the case without a traffic light and the other three are for traffic lights with different signals. From the first case, base profiles were built for the houses, using the typical energy consumptions of the electrical appliances mentioned in the surveys. Profiles were also created for each traffic light, which were compared with the base profile, to extract in this way the base of seven fuzzy rules. For the membership functions of the time sets and consumption variation, the use of fuzzy logics was proposed, which could not be carried out, but the experiment to be carried out was proposed, which consists of delivering signals to consumers. programmed for a period of time, to extract the behaviour they have against the signals, and thus use this data to adjust the parameters of the membership functions. In summary, a demand prediction module based on Takagi and Sugano fuzzy modelling was carried out, to whose identification stages stability analysis was added, which presented less error than the model with neural networks also designed for the same microgrid. In addition, a prediction was made for the dynamic load displacement factor, to be used in the demand management of the micro-network and a methodology was proposed to model the behaviour of consumers in the face of demand management signals. These three works contribute to the best performance of the micro-grid based on renewable energies, since they focus on one of the main problems, which corresponds to the uncertainty represented by the unconventional renewable energy sources on which these systems are based.

6.3 FUTURE WORK

proposals for future work that may be useful for the development of smart microgrids. The first is related to carrying out the experiment with the pulse counters and the programmed demand management signals, in order to be able to adjust the parameters of the proposed Mamdani fuzzy model. In this way, by having the fuzzy sets tuned, it is possible to test online over the microgrid and analyse if the optimization improves by taking into account the impact that demand management has on the demand prediction. Also, in relation to the demand prediction, it is proposed to analyse the training frequency every 3 months, coinciding with the seasonal changes, having at least one year of demand data, to determine if the seasons affect the prediction model. In order for the change of season to be reflected in the data, the training must be carried out with data from that station, therefore, it can also be analysed with how much data from that station a model that makes good demand predictions is obtained. Regarding demand management, it is proposed to use the water pump as a controllable load in the future. This load can be used when the displacement range is very limited, therefore there is little flexibility to displace the demand. Finally, in this work fuzzy intervals are used to determine the load displacement range. It is proposed to use fuzzy intervals to strengthen the micro-grid energy management system, so that the uncertainty of parameters such as solar power prediction, wind power prediction and demand prediction is taken into account in the optimization. In addition, it is proposed to study how changes in the displacement factor influence the useful life of batteries.

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