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THE APPLICATION Of FUZZY SYSTEM TO PREDICTION OF THE AMOUNT OF EMISSIONS FROM AN EMITTER ACTIVITY TO REDUCE CLIMATE CHANGE

Shwan Hikmat Sedeeq ABDLWAHAAB AGHA

Master's Thesis

Supervisor

Prof. Dr. Hasan Hüseyin BALIK

Istanbul, 2023

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The thesis titled THE APPLICATION OF FUZZY SYSTEM TO PREDICTION OF THE AMOUNT OF EMISSIONS FROM AN EMITTER ACTIVITY TO REDUCE CLIMATE CHANGE prepared by SHWAN HIKMAT SEDEEQ ABDLWAHAAB AGHA and submitted on 17/04/2023 has been **accepted unanimously** for the degree of Master of Science in Information Technologies.

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

Shwan Sedeeq Abdlwahaab AGHA

Signature

DEDICATION

To my father, my Inspirational, role model. May GOD have mercy on his soul…

To my mother, the one who is always by my side. God bless her and keep her healthy...

To my wife who always supported me…

To my daughter, the joy of my life…

To my brother and sisters who always pray for me…

To all my friends, those who were so generous to help me…

To all those people... I dedicate this work effort…

PREFACE

The research presented in this thesis was conducted under the guidance and support of my supervisor Prof. Dr. Hasan Hüseyin BALIK, whose expertise, encouragement, and guidance have been invaluable to me throughout this process. I am grateful for his unwavering support and dedication to helping me achieve my academic goals.

I would also like to express my gratitude to my family and friends for their unending help, inspiration, and motivation throughout my academic career. Throughout the difficult times, I have found strength in their support and love.

Finally, I hope that this thesis will contribute to the ongoing discussions, debates, and research in the field of predicting the amount of emissions and provide insights and recommendations that can inform future research and practice.

ABSTRACT

THE APPLICATION OF FUZZY SYSTEM TO PREDICTION OF THE AMOUNT OF EMISSIONS FROM AN EMITTER ACTIVITY TO REDUCE CLIMATE CHANGE

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Understanding the connections between CO2 emissions regarding the fuel consumption and the climate change may assist countries to determine the amount of CO2 or CO2 equivalent emissions and act accordingly by re-formulating new policies regarding energy to reduce these emissions and achieving sustainable development.

By creating a useful model using an adaptive neuro-fuzzy inference system (ANFIS) with multiple inputs, this research will serve as a foundation for future studies regarding other sectors responsible for CO2 or CO2 equivalent emissions, such as (industrial sector, agriculture, waste management, transportation, and other activities). This model will be able to predict the amount of emissions caused by vehicles. In this situation, the ANFIS model has been used along with prediction models based on actual data to forecast CO2 emissions based on three essential input indicators, engine size, number of cylinders, and fuel consumption, and correlate it with the amount of emissions.

Keywords: Climate Change, Prediction, CO2 Emissions, ANFIS, Fuzzy Inference System, Extra Trees Regressor, Green House Gases (GHG).

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ABBREVIATIONS

AI : Artificial Intelligence

ML : Machine Learning

FIS : Fuzzy Inference System

ETR : Extra Tree Regressor

RDT : Randomized Decision Trees

ANN : Artificial Neural Network

GHG : Green House Gases

MF : Membership Function

R : Correlation Coefficient

IPCC : Intergovernmental Panel on Climate Change

SPI : Standardized Precipitation Index

GL : Least Square Estimator

GA : Genetic Algorithm

BP : Back Propagation

PE : Processing Element

ANFIS : Adaptive Neuro-Fuzzy Inference System

RMSE : Root Mean Square Error

SDGs : Sustainable Development Goals

1. INTRODUCTION

1.1 BACKGROUND

The emissions of the greenhouse gases (GHG) that leads to climate change problem is considered as one of the most frequently stated problems within the 21'st century, as it plays a vital role in affecting almost every sector in the globe starting from economy ending with the way we live our lives in the present and the future, this issue can be extremely harmful to human beings as well as other species.

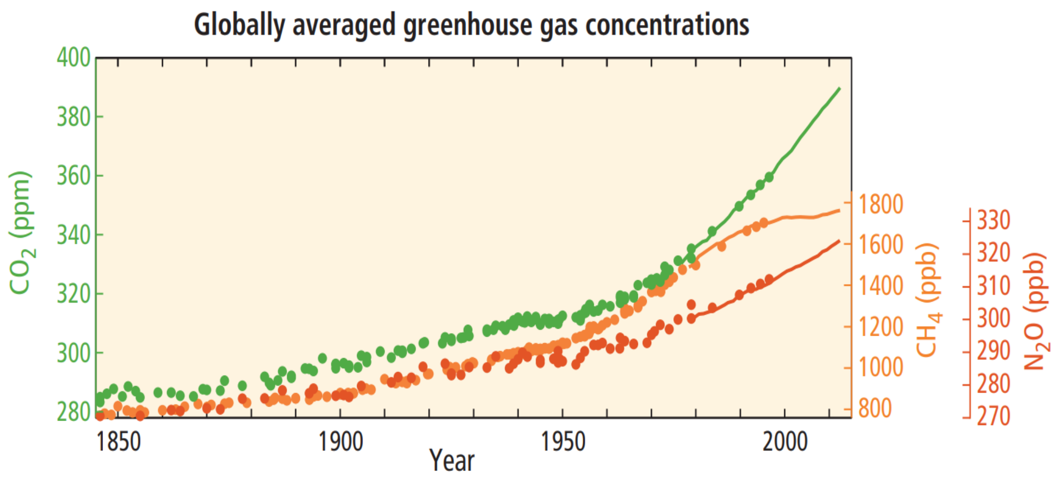

Figure 1.1: Globally Averaged Greenhouse Gas Concentrations (The Increasing In The Average Of CO2 Emissions Through The Last Decade) [22]

Results from earlier studies demonstrate a strong and consistent association between climate change and the noted points.

a. The rising of maximum and minimum temperatures.
b. The rising of sea levels.
c. Thawing permafrost.

The evidence of what we mentioned above is what we are witnessing everyday around the globe from severe weather temperature, huge size hurricanes, floods and wild fires in forests, land degradations and desertification and many other issues.

1.1.1 Global Warming

It is necessary here to clarify exactly what is meant by global warming. Historically, there has been an increasing and decreasing in the temperature of earth. And it all depends on how much sunlight does the earth receives. Within the past century, there has been another factor that affected the normal increment and decrement of the planet's temperature causing the climate change. This shows a need to be explicit about exactly what will be the situation within the next century. There are many other questions to be asked like, how much more the climate will be changing? And how to reduce the climate change

The PESETA research project's final report [1] on the effects of climate change in Europe provides a summary of recent studies to identify possible effects of climate change. Those impacts include agriculture, river floods, coastal system, tourism, human health, economy.

While Peterson et al., 2008 [2] summarize the consequences of climate change on the transportation sector in the United States, highlighting the repercussions of an increase in hot days, drought, sea level change, tropical storms, and seasonal shifts.

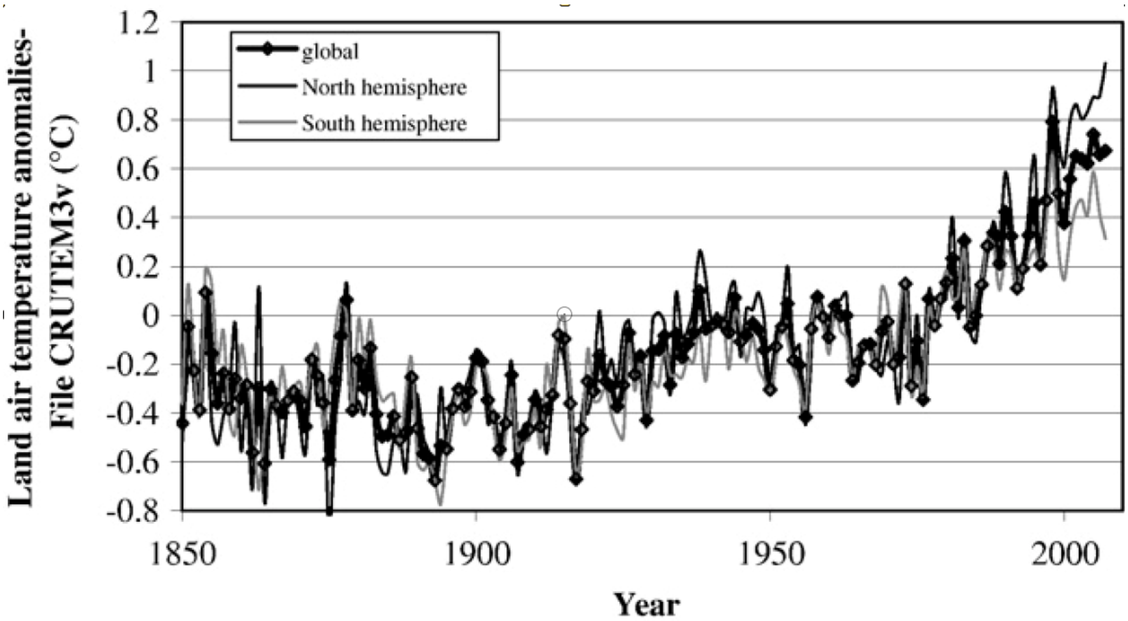

Figure 1.2: Rate of Temperature Increase Through The Last Decade [4]

Figure 1.1 shows the global, northern, and southern hemisphere land air temperature anomalies from 1850 to 2007. Despite seasonal variations, the average surface temperature worldwide is increasing. Starting from the twenty-first century.

1.1.2 Policies Regarding Climate Change

As per Beg et al.'s (2011) research, Climate change and sustainable development are connected, and it is likely that developing nations will suffer the most from it. Despite this, policies of developing countries do not primarily emphasize climate change as a significant requirement. Consequently, these countries experience considerable difficulties in adapting to the impacts of climate change, which hinder their development process. Nevertheless, certain synergies between climate change measures and the sustainable development goal, including energy efficiency, renewable energy, transport, and sustainable land-use policies, exist in developing countries. Although policymakers have paid minimal attention to this issue, implementing climate change policies may substantially benefit the local ecosystem.

It is for that reason, countries with low economic capabilities tend to not having a leading sector of transportations, in addition, lacking developed road network causing traffic jams which leads to increasing the CO_2 emissions caused by vehicles exhausts.

1.1.3 Emissions From Vehicles

A significant contributor to climate change is the carbon dioxide (CO_2) emissions from vehicles. Burning fossil fuels like gasoline and diesel results in significant CO_2 emissions into the atmosphere, which traps heat and contributes to global warming. One of the proposed approaches to reduce CO_2 emissions from vehicles is to switch to electric vehicles. In addition, electric vehicles are often more efficient than their gasoline-powered counterparts, which means they use less energy and produce fewer emissions per mile.According to experts, new cars will be able to drive themselves in some situations within five to ten years, and in the majority of situations within ten to twenty years. By changing travel demand, vehicle design, operating profiles, and fuel preferences, automation may have both positive and negative effects on road vehicle energy consumption and greenhouse gas (GHG) emissions [51].

Another way to reduce CO_2 emissions from vehicles is to improve the fuel efficiency of gasoline-powered vehicles. This can be done through the use of technologies such as hybrid engines, which combine a gasoline engine with an electric motor, and through the development of more efficient internal combustion engines.

1.2 AIMS AND OBJECTIVES

The key objective of this dissertation is to find solutions to reduce the effects of climate change by exploring the scope and nature of the problem of carbon dioxide emitted from vehicles.

Overall, addressing the problem of carbon dioxide emissions from vehicles will require a combination of technological, behavioral, and policy changes. By exploring the scope and nature of this problem, and identifying and implementing possible effective solutions, it is possible to significantly reduce the impact of transportation on climate change.

The goal will therefore be building a model that can predict the amount of emissions, it will be based essentially on automatic natural language processing and machine learning. And it will be targeting precisely the amount of CO_2 emissions from vehicles.

Basically, the results will represent an estimation for carbon emissions amount and it will not show the exact amount of emissions due to different circumstances.

1.3 PROBLEM STATEMENT

The field of climate change research has witnessed an upsurge in recent years, receiving significant attention from academia, decision-makers, and prominent IT corporations. As climate change is a worldwide issue, every nation bears the responsibility of mitigating it by curbing carbon emissions, which are deemed the primary driver of the "greenhouse effect." Given that vehicle emissions are known to be a major factor in global warming and climate change, reducing carbon dioxide emissions from vehicles are crucial in addressing this challenge.

Figure 1.3: Impacts of Climate Change [4].

1.4 CONTRIBUTION

As part of this study, employing machine learning algorithms and technologies to build a model with the ability of predicting the amount of carbon emissions. There are several important areas where this study makes an original contribution to the efforts of detecting the size of the issue that governments are dealing with. A close estimation to the current amount of CO_2 emissions can and will play a major role in visualizing the risks that will be confronted in the future if no clear decisions towards reducing the global warming was taken.

The ANFIS model offers precise and dependable forecasts, possesses the capacity to adjust and conform to varying conditions, and aids in the worldwide endeavor to counteract climate change. In order to reduce emissions and manage the environmental impact of the transportation sector, which continues to be a significant contributor to the emission of greenhouse gases, it is increasingly crucial to use precise prediction models.

1.5 THESIS ORGANIZATION

Following are the elements of the thesis structure, we will look at some of the earlier research and work on climate change in this section of the thesis. We shall give a brief summary of each component in the following sentences. In Section 4, we provide a thorough explanation of our methodology, and in Section 5, we will go through the conclusion and the future work. we implement our model and report the outcomes. We'll look at how everything will work together in the next years in the sixth section.

2. LITERITAURE REVIEW

2.1 INTRODUCTION

Both academic and commercial interest in machine learning is growing as a result of problems including climate change, desertification, degradation, global warming, and biodiversity loss. Researchers in machine learning algorithms can employ these algorithms for the use of analysing big amounts of data gathered within previous years. Different algorithms of machine learning have been proven to be effectively sufficient especially when dealing with large scale datasets. The simplicity of applying these algorithms to a large-scale dataset may provide an extensive solution to a better understanding to some complicated issues such as the issues mentioned above. Researchers should be able to investigate ways for identifying the efficient techniques to use to estimate the scale of the effects of climate change. Then verifying these effects, categorize each of these effects according to the impact it marks, developing policies to adapt to these impacts while mapping a clear future roadmap to reduce climate change. Although findings of recent research have shown that artificial intelligence technologies like machine learning can be considered as an efficient technology to help analyzing, classifying and processing big data related to climate change, there is still work to be done to enhance the field.

2.2 RELATED WORKS

Recent advances in artificial neural network and fuzzy logic research have been utilized increasingly in a corresponding effort to improve predictions in various fields. Among these technologies, Adaptive Neuro-Fuzzy Inference System (ANFIS) has emerged as a powerful technique, allowing for the prediction of complex phenomena and complex behavior.

S.Hoda Rahmati et al. in their study compared between ANFIS, ANN, multivariable regression and ARIMA methods to forecast the amount of urban water consumption per capita in Tehran / Iran. They were able to recognize the effects on climate change and they found that ANFIS model is more sufficient than other methods [5].

In their study on the relationship between CO2 emissions and global warming temperatures, Muhammad Zahir Khan et al. [6] attempted to accurately model the complex connections between variables by utilizing three advanced statistical tools: adaptive neuro-fuzzy inference systems, artificial neural networks, and fuzzy time series models. They aimed to avoid making strict assumptions in their analysis. The traditional statistical methods may lead to producing results with large margins of error.

In their study, H. Oubehar et al. describe the design and real-time implementation of a powerful adaptive neural-fuzzy inference system for controlling greenhouse climate. Fuzzy logic and artificial neural network techniques are combined in the authors' proposed system to improve the ability to track temperature and relative humidity references, which are crucial for crop growth. The fuzzy logic controller model created in MATLAB Simulink serves as the basis for the training datasets for the adaptive neural-fuzzy inference system, and its robustness has been experimentally confirmed. With regard to set point tracking, response time, robustness against variations in external parameters, non-linearity, and energy optimization, the proposed control system aims to achieve the best performance possible [7].

With data from the Bojnourd meteorological station covering the period from January 1984 to December 2012, Maryam Mokhtarzad et al. in their study [8] compared the effectiveness of three modeling techniques for predicting drought: artificial neural networks (ANNs), adaptive neuro-fuzzy interface systems (ANFIS), and support vector machines (SVMs). Temperature, humidity, and seasonal precipitation were taken into account as the study's input parameters, and the Standardized Precipitation Index (SPI) was used as the study's output. The results of this study show that the SVM model performs better in terms of predictive accuracy than the ANN and ANFIS models.

A study by Yanlai Zhou and colleagues sought to develop a reliable flood forecasting model, particularly for regions experiencing rapid urban development. The authors propose a recurrent Adaptive-Network-based Fuzzy Inference System (R-ANFIS) that combines a Genetic Algorithm and Least Square

Estimator to optimize model parameters for multi-step-ahead forecasts (GL). To reduce flood risks and offer useful information for decision-making, accurate flood forecasting is essential. The R-ANFIS(GL) model successfully simulates the intricate non-stationary rainfall-runoff process and incorporates observed rainfall and discharge data with the most recent model outputs, improving prediction accuracy [9].

It is crucial to take into account excessive rainfall, especially in tropical areas, in order to forecast flooding in flat or concave areas. One of the most rapidly developing cities with flooding problems, South Tangerang, was the subject of a study on critical points by Wayan Suparta et al. The authors used artificial intelligence methods like ANFIS to try and predict when it would rain (Adaptive NeuroFuzzy Inference System). This approach combines the neural network learning capabilities with the fuzzy system's transparent linguistic representation. The ANFIS model was created, trained, and tested to assess its performance using a variety of input structures and membership functions. With 80% of testing data correctly predicted, the results showed that rainfall prediction based on ANFIS time series is promising. Decision-makers can reduce the risks associated with flooding by using accurate and trustworthy multi-step-ahead flood forecasts [10].

There has been an increase in thunderstorm activity in the Mesoscale Convective System (MCS) region, which could be dangerous. The increased precipitation and dense cloud cover have been blamed for this phenomenon. Climate change is one of the factors causing this trend. Wayan Suparta and Wahyu Sasongko Putro [11] used Multiple Linear Regression (MLR), the Dvorak method, and the Adaptive Neuro-Fuzzy Inference System to quantify the extent of thunderstorm activity in the Tawau region of Sabah, Malaysia (ANFIS). They gathered meteorological data for their study, which included inputs for pressure, temperature, relative humidity, cloud cover, precipitable water vapor, and precipitation. The Jacobi algorithm's findings revealed a strong correlation between thunderstorms and relative humidity and precipitable water vapor. These two inputs were then used in conjunction with the Sugeno method to create a fuzzy inference system. The study's conclusions showed that the intermonsoon season was when thunderstorm activity peaked. The model's performance was assessed as well, and it was found that, with an error rate under 50%, it was as accurate as manually collected data.

Natural disasters are a persistent danger that endangers the survival of both people and wildlife. An important factor in minimizing and managing the negative effects of such events on living things and their surroundings is the timely detection of forest fires. Forest fires are a type of natural disaster that are frequently brought on by climate change. A forest fire prediction and management system that integrates the flower pollination optimization algorithm (FPO) and the Adaptive Neuro-Fuzzy Inference System [12] was proposed by Khaled Ahmed et al (ANFIS). To improve ANFIS training parameters' predictive accuracy, the FPO optimizes them. Six data sets were used to compare the proposed system's performance to three well-known algorithms: the Genetic Algorithm with ANFIS (GA-ANFIS), Particle Swarm Optimization with ANFIS (PSO-ANFIS), and basic ANFIS. A data set related to forest fires was also used to evaluate the system. The empirical results show that, when compared to other techniques, the FPO-ANFIS model performs better in terms of forecasted outcomes.

Research on climate change has become increasingly important as the energy sector has developed because it has a direct impact on the creation of alternative energy. A concerted effort has therefore been made to create predictive algorithms that can foresee the effects of climate on various energy production sites. In a similar vein, RUIZ Luis Carlos et al. [13] suggested using the Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm in conjunction with information from the NASA Langley research center's virtual database to analyze and forecast solar radiation in the region surrounding the Nueva Granada Military University campus in Cajicá, Colombia. Optimising the use of the area's power generation infrastructure was the aim of this project. If these predictive systems were to be successfully implemented, it would be possible to detect solar radiation in Colombia's various regions in a timely manner, allowing for the generation of enough electricity to satisfy local demand. The study's findings show that the approximation error for the model was less than 1%.

For the creation of accurate runoff forecast models, seasonal rainfall forecasting is essential. Large-scale climate modes that influence Australia's rainfall have recently been discovered to be helpful in predicting rainfall. For the first time in southeast Australia, Adaptive Network-based Fuzzy Inference System (ANFIS) models were developed in the study by F. Mekanik et al. [14] to forecast spring rainfall in east, central, and west Victoria. The suggested ANFIS models were compared to the Predictive Ocean Atmosphere Model for Australia (POAMA), traditional Artificial Neural Network (ANN) models, and climatology predictions. The ANFIS projections outperformed the ANN and climatology forecasts in the majority of regions. While ANFIS outperformed POAMA in terms of prediction errors and root mean square error skill score in west Victoria, POAMA outperformed it in terms of mean absolute error (MAE) and root mean square error (RMSE) in east and some of central Victoria (RMSEP). Overall, the case study's correlation coefficient demonstrated that ANFIS models delivered superior outcomes. The study comes to the conclusion that ANFIS is a potential tool for seasonal predictions in Australia due to its comparable accuracy with minimal inputs, quicker development time, and reduced complexity compared to dynamic models.

Omar Suleiman Arabeyyat's study [15] employed the Adaptive Neuro-Fuzzy Inference System (ANFIS) to anticipate Jordan's minimum and maximum temperatures as well as its annual rainfall for the ensuing ten years using data from 1985 to 2015. Using the correlation coefficient and mean square error, the models' effectiveness was assessed. The models were assessed using various optimization techniques, membership functions, and training/testing data ratios. The results showed that, in comparison to past studies, ANFIS was a trustworthy method for predicting rainfall temperatures throughout the ensuing ten years. The study also found that a predicted zone for both the minimum and maximum average annual temperatures would disappear during the following decade and that the average annual rainfall levels would drop, which is contradictory to actual data from 1985 to 2015.

In a study [16], Semih Kale tried to create an Adaptive Neuro-Fuzzy Inference System (ANFIS) model for the forecast of the sea surface temperature (SST) in the Anakkale Strait. The study used data on air temperature, evaporation, and precipitation from a nearby meteorological station. Both the grid partition method (ANFIS-GP) and the subtractive clustering partitioning method (ANFIS-SC) with Gaussian membership functions were used to create the Takagi-Sugeno fuzzy inference system. Six different criteria, including mean square error, root mean square error, mean absolute error, mean absolute percentage error, Nash-Sutcliffe efficiency, and correlation of determination, were used to assess the effectiveness of the constructed SST prediction models. The dataset was divided into training and testing sets, with the hybrid algorithm serving as the training algorithm, in order to train the ANFIS. The ANFIS-SC4 model showed the strongest correlation between the actual and expected SST values, with a coefficient of 0.96. The findings imply that predictions of sea surface temperature in other parts of the world may be possible using the developed ANFIS model.

Sanda Florentina Mihalache et al. used the adaptive neuro-fuzzy inference system (ANFIS) in their research study [17] to predict short-term particulate matter (PM) concentrations in urban areas of Romania. The prediction model developed by the authors was meant to be used to inform the public when PM concentration exceeded set limits and to provide information for knowledge-based modeling. The authors used three different datasets that covered all seasons. ANFIS was chosen because of its capacity to forecast urban air quality, which is crucial for understanding how particulate matter affects both human health and climate change.

In their study [18] for the prediction of short-term air temperature, Aliihsan Sekertekin et al. compared four different machine learning approaches: ANFIS with Fuzzy C-Means (FCM), ANFIS with Subtractive Clustering (SC), ANFIS with Grid Partition (GP), and Long Short-Term Memory (LSTM) neural network (AT). AT data from a solar power plant in Tarsus, Turkey, were used in the study. The accuracy of the models was assessed using metrics such as the correlation coefficient (R), mean absolute error (MAE), and root mean square error (RMSE). According to the findings, the LSTM neural network performed better than the other ANFIS models in terms of prediction accuracy for forecasts made an hour in the future as well as predictions made a day in the future.

Dr. Falguni Parekh and colleagues used the Adaptive Neuro Fuzzy Inference System to create models for predicting monthly monsoon rainfall in the Gandhinagar station in a study [19]. (ANFIS). Eight models had to be created for the investigation utilizing different membership functions and meteorological inputs. It was shown that the hybrid method, which employs seven membership functions and three input variables (temperature, relative humidity, and wind speed), produces the best outcomes for predicting rainfall in the area. The effectiveness of the constructed models was assessed using the four assessment criteria RMSE, correlation coefficient, coefficient of determination, and discrepancy ratio. According to the study, ANFIS has the potential to be a helpful tool for forecasting rainfall in the Gandhinagar station.

3. MATERIALS AND METHODS

3.1 INTRODUCTION

For more than a century, fossil fuels, such as coal, oil, and natural gas, have been the principal energy sources for the world. However, the adverse environmental impacts associated with burning these fuels have been a growing concern. Nevertheless, fossil fuels continue to significantly contribute to supplying the world's energy needs, and they still constitute a substantial portion of the primary energy consumption globally. Specifically, in 2019, oil, natural gas, and coal accounted for approximately 78% of the world's total energy consumption [20].

There are several reasons why fossil fuels remain in high demand. One of the main reasons is their availability and affordability. Fossil fuels are found in large quantities in many parts of the world, and the extraction and transportation of these fuels is well-established and relatively cheap compared to other sources of energy. This makes them an attractive option for countries and industries looking to meet their energy needs at a low cost.

Another reason for the continued reliance on fossil fuels is the fact that they are a highly efficient source of energy. Oil, natural gas, and coal can be burned to generate large amounts of electricity, heat, and transportation fuel. This makes them a key part of many industries, including power generation, transportation, and manufacturing [69].

Additionally, fossil fuels have a high energy density, which means that they can store a lot of energy in a small space. This is important for transportation, where weight and space are major considerations. Fossil fuels also have a relatively high energy return on investment, which means that the energy obtained from burning these fuels is greater than the energy required to extract and process them.

Despite the fact that we still rely heavily on fossil fuels, we are starting to understand how critical it is to switch to cleaner, more sustainable energy sources. The burning of fossil fuels results in the release of greenhouse gases such as carbon dioxide into the atmosphere, hastening climate change. The burning of fossil fuels, according to the Intergovernmental Panel on Climate Change (IPCC), is the primary cause of climate change, and it is crucial to reduce this consumption to lessen the negative effects of climate change [21].

Globally, many fossil fuel substitutes are now being developed and implemented, including solar, wind, and hydroelectric power. These energy sources face challenges such high costs, instability, and constrained scalability despite having the potential to dramatically cut greenhouse gas emissions. The rate at which we are moving away from fossil fuels is insufficient, notwithstanding our continued efforts in this direction. Accelerating the use of renewable energy and gradually phasing out the usage of fossil fuels are essential in order to address the urgent requirement for reducing greenhouse gas emissions and reducing the effects of climate change. Governments, corporations, and individuals must work together to achieve this aim, and significant funds must be invested in renewable energy infrastructure and technologies. However, this transition's long-term benefits, such as a healthier planet and a more sustainable future, make it an important and worthwhile endeavor [68].

According to Noreen Beg and colleagues, countries that significantly rely on fossil fuels for economic growth and employment may be at risk from mitigation attempts to keep global warming below 1.5°C. These dangers could take the shape of a reduction in the demand for these resources on a worldwide scale, which would affect mining operations and export earnings, as well as the necessity of a rapid decarbonization of home economies. Targeted actions to diversify economies and move away from fossil fuels may be required [25] to reduce these risks. Although there is an increasing need to lessen reliance on fossil fuels, they continue to be an essential source of energy for the modern world. Climate-resilient development pathways (CRDPs) can assist in achieving the twin objectives of encouraging sustainable development and reducing global warming to 1.5°C. It is possible to strengthen adaptation efforts and create a more resilient world by putting into action policies that support the Sustainable Development Goals (SDGs), reduce greenhouse gas emissions, and restrict global warming.

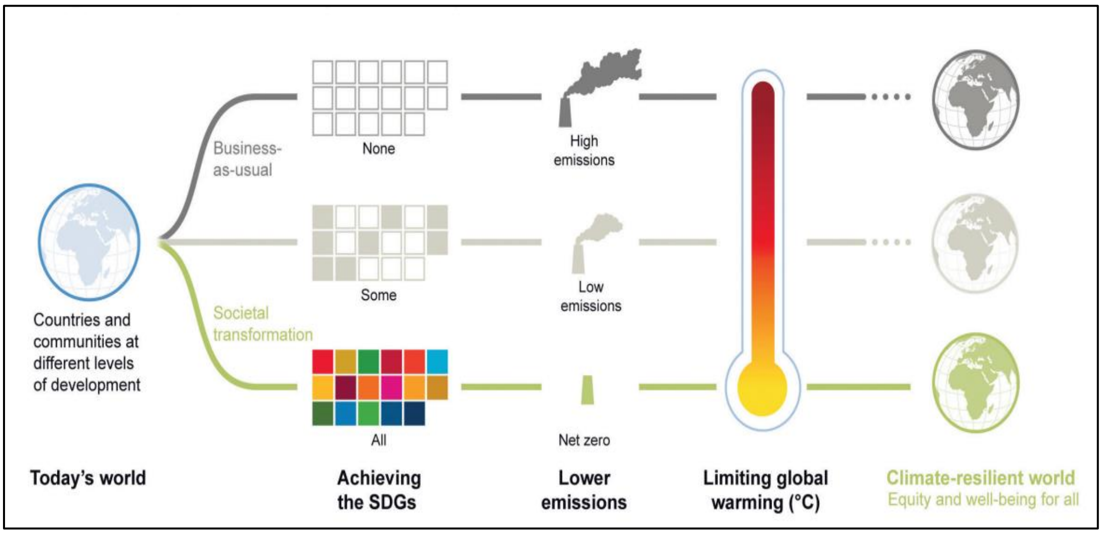

Figure 3.1: Climate-Resilient World [21].

3.1.1 Major Contributors to Climate Change

There are several sectors that contribute significantly to climate change, including:

a. Energy: The energy industry is recognised as a substantial contributor to the phenomenon of climate change due to its significant greenhouse gas emissions. According to the Intergovernmental Panel on Climate Change (IPCC), the energy sector is believed to be to blame for 70% of global greenhouse gas emissions. Fossil fuels, which include coal, oil, and natural gas and are the main types of energy used worldwide, are principally responsible for this outcome. Carbon dioxide (CO2) is emitted into the atmosphere when fossil fuels are burned, which contributes to global warming. This prevents solar heat from escaping into space again by absorbing and encasing it in CO2. The earth's temperature will increase in direct proportion to the amount of CO2 released into the atmosphere. Methane and nitrous oxide are two other greenhouse gases that are released by the energy sector and that also play a role in climate change. Additionally potent heat-trapping gases, these gases' emissions also have an impact on global warming. As a result of not emitting greenhouse gases, other renewable energy sources like solar, wind, and hydropower do not contribute to climate change. The fight against climate change must therefore prioritize the switch to renewable energy. The advantages of this transition are obvious, but it requires substantial investment and policy changes. We can slow the rate of global warming and lessen its negative effects by reducing greenhouse gas emissions brought on by the energy sector. In conclusion, switching to renewable energy is essential to addressing this global crisis because the energy sector contributes significantly to climate change. Recognizing the contribution of the energy sector to climate change and taking action to reduce greenhouse gas emissions are crucial for both policymakers and individuals.

Figure 3.2: Energy Sector [26].

b. Transportation: It was mentioned that one of the main contributors to climate change is the transportation sector because of its large role in the world's greenhouse gas emissions. According to the Intergovernmental Panel on Climate Change (IPCC), the transportation sector was accountable for 14% of all energy-related carbon dioxide emissions globally in 2010, and it is anticipated that this percentage would increase over the ensuing decades (IPCC, 2014). The transportation industry is a major source of carbon emissions, and the use of fossil fuels like gasoline and diesel to power automobiles plays a key role in this. These fuels release carbon dioxide into the atmosphere when they are burned, which adds to the general increase in global temperatures. The transportation sector also generates nitrous oxide and methane, two more greenhouse gases that contribute to global warming. The need for transportation is increasing, particularly in nations that are expanding quickly, and this is leading to an increase in the sector's carbon emissions. Due to society's increasing urbanization and globalization, there are more cars on the road and they go farther. It is projected that this tendency will continue in the ensuing decades, escalating the problem of climate change. There are several ways the transportation sector can reduce carbon emissions and mitigate climate change. Switching to cleaner alternative fuels, such as hydrogen or electricity, which greatly cut emissions when used in motor vehicles, is one option. Another choice is to encourage people to use public transportation and carpooling, which can lessen both the overall number of vehicles on the road and the distance that each individual vehicle travels. Overall, it is evident that the transportation industry contributes significantly to climate change and that lowering its carbon emissions is crucial to reducing the effects of global warming. It is possible to lessen the sector's carbon footprint and slow the rate of climate change by implementing cleaner fuels and encouraging sustainable transportation methods [51].

c. Industrial processes: The burning of fossil fuels for energy is a major source of greenhouse gas emissions, which has long been acknowledged as being a key cause of climate change in the industrial sector. The Intergovernmental Panel on Climate Change estimates that in 2010 the industrial sector contributed around 21% of the world's carbon dioxide emissions [22]. The combustion of fossil fuels for energy is one of the main ways that the industrial sector contributes to climate change. Using coal, oil, and natural gas to run factories and other industrial operations is a prime example of this. Carbon dioxide and other greenhouse gases are released into the atmosphere through the combustion of these fossil fuels, trapping heat and causing global warming. The manufacture of cement is a substantial source of greenhouse gas emissions from the industrial sector. Cement manufacture requires a lot of energy and produces a lot of carbon dioxide as a byproduct. In actuality, the cement sector is in charge of 5% of the world's carbon dioxide emissions [23]. The industrial sector also contributes to climate change by releasing additional greenhouse gases, such as methane and nitrous oxide, in addition to carbon dioxide emissions. Natural gas production and transportation releases methane, whereas the manufacture of synthetic fertilizers and other chemicals releases nitrous oxide. The effects of industrial operations on climate change are vast and diverse. Heat waves, droughts, and other extreme weather events could become more frequent and severe as a result of rising global temperatures, which could have a negative effect on people's health and well-being. The distribution of diseases can shift as a result of climate change, causing both the development of new diseases and the resurgence of established ones. It is essential to take action to reduce greenhouse gas emissions from industrial operations given the industrial sector's substantial role in climate change.

d. Waste: The waste industry significantly contributes to climate change. The Intergovernmental Panel on Climate Change (IPCC) estimates that the waste sector is responsible for 3.5 percent of global greenhouse gas (GHG) emissions, coming in fourth place behind the energy, industrial processes, and agricultural sectors. [22]. The waste sector generates GHG emissions through three main pathways: landfills, waste incineration, and organic waste decomposition. Landfills are the largest contributor to GHG emissions in the waste sector, accounting for approximately 60% of total emissions [22]. Landfills release methane, a potent GHG, as organic matter decomposes in the absence of oxygen. Waste incineration is the second largest contributor to GHG emissions in the waste sector, accounting for approximately 30% of total emissions [22]. The combustion of fossil fuels needed to power the incineration process as well as the waste itself produce carbon dioxide (CO2) emissions during the incineration of waste. Methane and CO2 emissions are produced during the decomposition of organic waste in open landfills and uncontrolled composting facilities [22]. In addition to GHG emissions, the waste sector also has a significant impact on climate change through the production and transportation of materials. The extraction, transportation, and processing of raw materials for the production of goods generates GHG emissions and contributes to climate change. The waste sector plays a role in this process by consuming resources and contributing to the production of goods through the recycling and reuse of materials. The transportation of waste to landfills and incineration facilities also generates GHG emissions. There are several actions that can be taken to reduce the impacts of the waste sector on climate change. These include increasing recycling and reuse rates, reducing the amount of waste generated, and improving waste management practices. The implementation of these actions can not only reduce GHG emissions from the waste sector, but also reduce the demand for raw materials and energy, ultimately contributing to a more sustainable and low-carbon economy.

e. Land-use and land-use change: A major factor in climate change is the phrase "land use and land use change," which refers to how land is used and the changes that take place to it through time. Agriculture, urbanization, and land use changes like deforestation can all have a big impact on the climate. Emissions of greenhouse gases are one of the primary ways that land use and land-use change affect climate change. When forests are removed for farming or urban development, the carbon stored in the trees is released into the atmosphere, increasing the amount of greenhouse gases in the atmosphere. Similar to this, the use of fossil fuels in tractors and other equipment is another factor in the emission of greenhouse gases in agriculture. Through changes in land use and land use change, modifications to the Earth's surface can also affect climate. Urbanization, for instance, can result in the destruction of natural habitats and the development of heat islands, which can raise local temperatures. Furthermore, regional and local weather patterns as well as the world's water cycle can be impacted by deforestation. In addition to these direct effects, changes in land use and climate can also result from indirect effects. For instance, raising livestock for human consumption is a large source of greenhouse gas emissions, and this activity is strongly linked to land use. Overall, it is evident that changes in land use and their effects on climate change are significant, and addressing this issue will be essential in efforts to lessen and prepare for the effects of a changing climate [24].

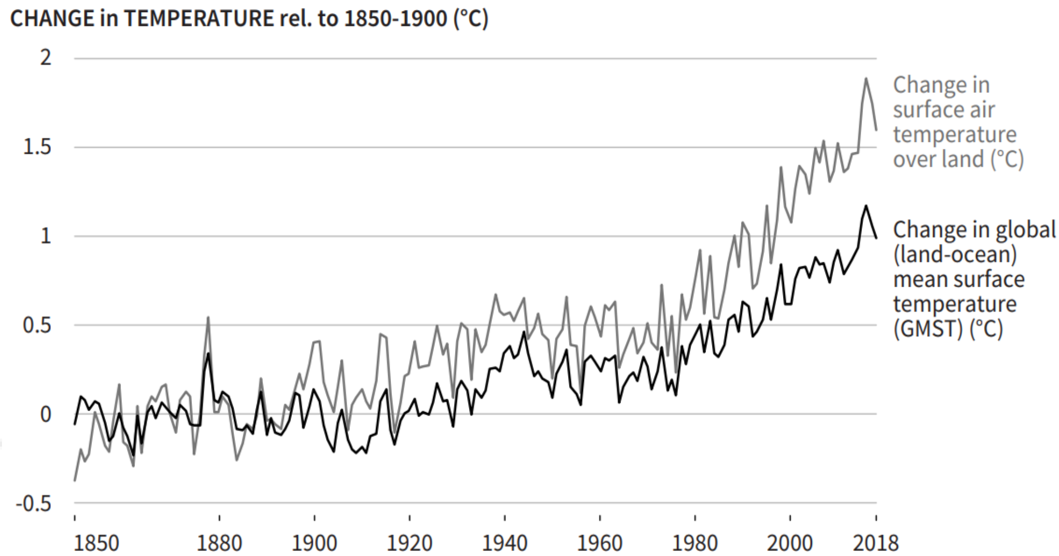

Figure 3.3: Change In Surface Air Temperature 1850 – 2018 [24].

The increase in greenhouse gas concentrations in the atmosphere caused by human activity, which is what causes climate change, is largely attributed to these industries. The reduction of emissions from these industries is necessary for society to mitigate the effects of climate change.

Figure 3.4: Waste Management Threat, Image By: Victor Vergararamachandra Jammi [27].

3.2 ARTIFICIAL INTELLIGENCE

Artificial intelligence (AI) is the ability of computers and other machines to carry out tasks that typically require intelligence akin to that of a human, such as problem-solving, learning, and judgment [28]. In recent years, artificial intelligence (AI) has experienced rapid growth. It has a wide range of applications in industries like healthcare, finance, education, and transportation.

AI's capacity to accurately and quickly process large amounts of data is one of its main advantages. This allows for the automation of tasks that are time-consuming or difficult for humans to perform, such as analyzing medical records or detecting fraudulent activity. AI can also help to improve efficiency by identifying patterns and trends that humans might miss. By offering real-time analysis and recommendations based on data, AI has the potential to enhance decision-making. For instance, AI can be used to forecast customer behavior or to improve supply chain management. However, it is important to note that AI systems can only be as accurate as the data they are trained on, and there are concerns about the potential for biased or unethical decision-making if the training data is not diverse or representative. There are also concerns about the potential for job displacement as AI becomes more prevalent in the workforce. While some jobs may be automated, there is also the potential for new job creation in areas such as AI development and maintenance. It is important for policy makers and businesses to consider the potential impacts of AI on employment and to invest in training and education programs to prepare the workforce for the changing job market [60].

Overall, AI has the potential to bring significant benefits in terms of efficiency, accuracy, and decision-making. But it's crucial to take into account the potential effects and make sure that the creation and application of AI systems is transparent, moral, and responsible.

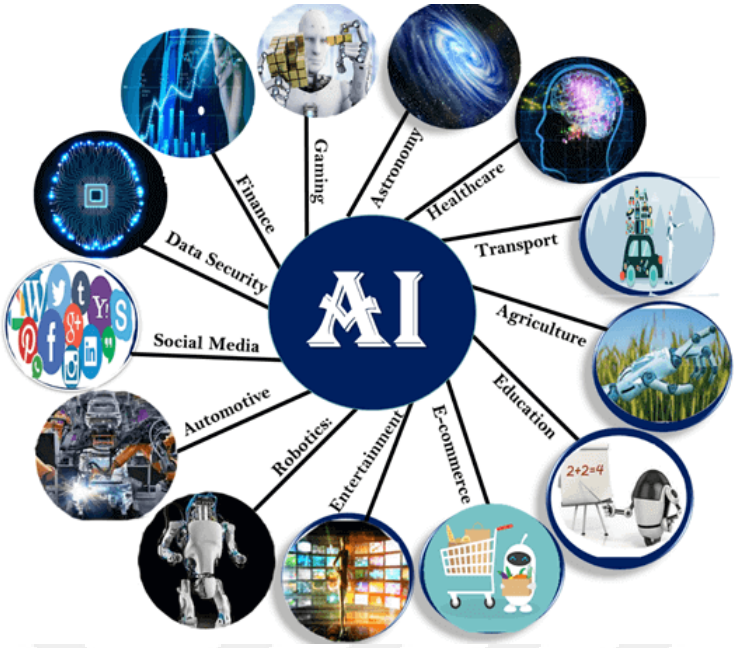

Figure 3.5: Applications of AI [45].

3.2.1 Artificial Intelligence and Climate Change

Artificial intelligence has the potential to significantly assist with the issues brought by climate change (AI). Machine learning and other artificial intelligence techniques can be used to analyze enormous volumes of data and identify patterns that can be utilized to inform the development of more effective policies and strategies for mitigating and preparing for the effects of climate change. Predicting and simulating the effects of climate change is one area where AI can be especially helpful. For instance, data on weather patterns, atmospheric and oceanic conditions, and other elements that affect the Earth's climate can be analyzed using AI algorithms. Researchers and policy makers can better grasp how various scenarios can play out in terms of temperature, sea level rise, and other important indicators by using AI systems to analyze this data [29].

AI can be used in other aspects of managing climate change, such as renewable energy and carbon capture, in addition to prediction and modeling. AI algorithms, for instance, can be used to maximize the efficiency and minimize the carbon footprint of renewable energy systems like solar and wind farms. Similar to this, AI can be used to determine the best methods and tools for capturing and storing carbon emissions, lessening their impact on the environment. In general, artificial intelligence (AI) has the potential to dramatically improve our knowledge of and capacity to combat climate change. We may increase our understanding of the causes, effects, and tactics for mitigating and adapting to climate change by utilizing the capabilities of machine learning and other AI techniques [51].

3.2.2 Machine Learning Algorithms

Computers can learn from data and make predictions or decisions without being explicitly programmed thanks to machine learning algorithms, a subset of artificial intelligence. To make predictions and enhance decision-making processes, these algorithms are applied in a number of industries, such as manufacturing, healthcare, and finance.

One of the key benefits of machine learning algorithms is their capacity to efficiently process and evaluate massive amounts of data. Businesses can thus discover new information and make predictions that might otherwise be challenging or impracticable. Machine learning algorithms, for instance, can be used to forecast stock prices, identify trends in medical data, or enhance production processes.

Machine learning algorithms can be categorized into supervised learning, unsupervised learning, and reinforcement learning algorithms, among others [59].

3.2.3 Supervised Learning Algorithms

In supervised learning, a model is trained to make predictions or decisions based on examples that have been labeled. The goal of supervised learning is to create a function that converts input data into output data using a set of labeled training examples [30]. The function can then make predictions or decisions based on new, unforeseen data. The two types of supervised learning algorithms are regression and classification. A continuous output value, like the cost of a home or the temperature of a sensor, can be predicted using regression algorithms. A discrete output value, such as the type of illness or the tone of a review, can be predicted using classification algorithms. Several supervised learning methods include logistic regression, support vector machines, decision trees, and linear regression [31]. The way these algorithms model the function and optimize the parameters is different. In contrast to support vector machines, which optimize the parameters using a kernel function and a quadratic approach, linear regression uses a linear function and the least squares method. However, supervised learning is also subject to some limitations. It calls for a substantial amount of labeled examples, which can be expensive and time-consuming to acquire. It might also be sensitive to the caliber and variety of the examples with labels. The model may perform well on training data but poorly on test data when there is over-fitting.

3.2.4 Unsupervised Learning Algorithms

Machine learning techniques such as unsupervised learning are used to train models to find structures or patterns in data without the aid of labeled training data. Instead of making predictions or decisions based on labeled examples, unsupervised learning aims to uncover hidden structures or relationships in the data [30]. Clustering and dimensionality reduction are two categories into which unsupervised learning algorithms can be divided. Clustering techniques are used to separate the data into groups or clusters based on how similar the data points are. Dimensionality reduction methods are used to reduce the number of dimensions, or features, in the data while preserving the most crucial information. Unsupervised learning algorithms come in a variety of forms, including k-means, hierarchical clustering, principal component analysis, and auto-encoders. These algorithms differ in the way they measure the similarity of the data points and the way they optimize the parameters. For example, k-means uses a Euclidean distance measure and an iterative optimization method to optimize the parameters, while auto-encoders use a reconstruction error measure and a gradient descent method to optimize the parameters. Unsupervised learning also has some limitations. It may not make as accurate predictions or decisions as supervised learning, because it does not use labeled examples to guide the learning process [31].

3.3 FUZZY INFERENCE SYSTEM (FIS)

An example of a computational intelligence tool used to model and manage complex systems is fuzzy inference systems (FIS). A mathematical framework for representing and processing ambiguous, imprecise, and incomplete data. FISs have been widely used in various fields, including control engineering, decision making, pattern recognition, and data mining [32].

3.3.1 Structure of Fuzzy Inference System (FIS)

FISs consist of three main components:

a. Fuzzy rule base.
b. Fuzzy inference engine.
c. Defuzzification module.

The system's knowledge and experience are reflected in the fuzzy rule base as statements that use ambiguous phrases like "extremely," "slightly," and "somewhat" to express the relationships between input and output variables. For a temperature management system, one example of a fuzzy rule may be, "If the temperature is very cold, boost the heating." The input values, fuzzy rules, and fuzzy inference engine are used to generate inferences and output values. To combine the rules and inputs and produce the output, a series of fuzzy operations, including union, intersection, and complement, are used [33]. The defuzzification module transforms the ambiguous output into a clear value that the system can use. FISs have a number of benefits over conventional systems. They can handle data ambiguity and imprecision and base conclusions on conflicting or partial facts. Second, they can process multiple inputs and outputs simultaneously and handle complex relationships between variables. Third, they are flexible and can be easily modified or updated with new rules and knowledge.

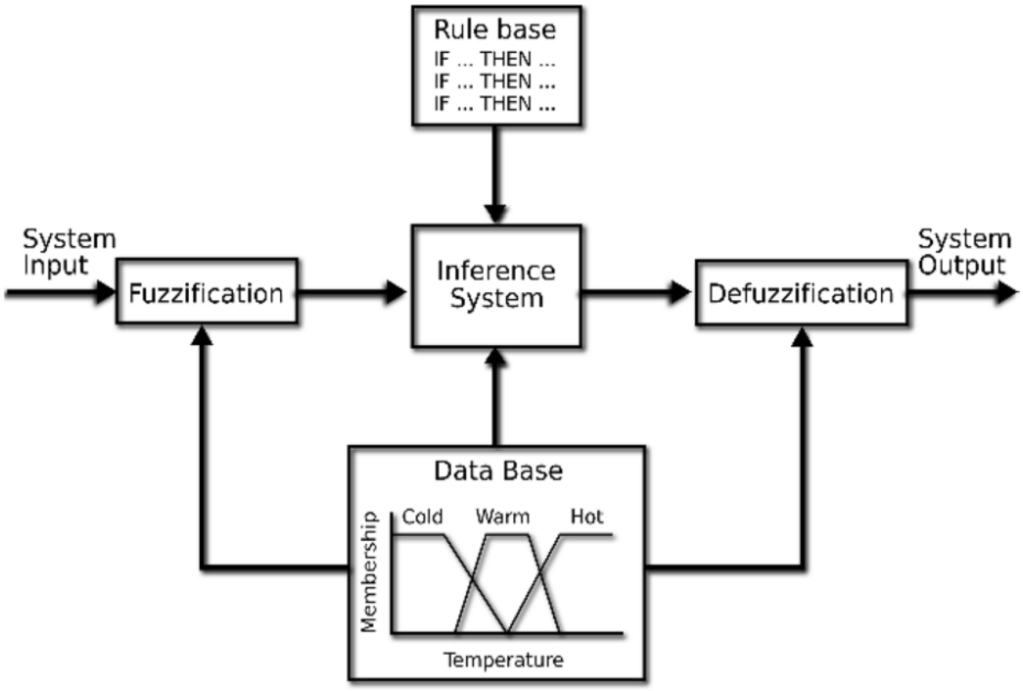

Figure 3.6: Fuzzy Inference System [34].

3.3.2 Fuzzy Inference System Membership Functions and Rules

However, FISs also have some limitations. They may require a large number of rules to model a complex system, which can make the rule base difficult to manage and maintain. They may also be sensitive to the choice of membership functions, which define the fuzzy sets used in the rules. Choosing inappropriate membership functions can affect the accuracy and performance of the FIS. It has been acknowledged that FISs are a powerful and practical tool for simulating and managing complex systems. They can manage data uncertainty and imprecision and handle multiple inputs and outputs at once. However, they might need a lot of regulations, and they might be strict about the membership functions [58].

A collection of fuzzy rules that define the connections between the inputs and outputs of the FIS make up the fuzzy rule base. Every fuzzy rule is expressed in the following way: "IF input1 is A AND input2 is B AND input3 is C THEN output is D," where A, B, C, and D are fuzzy sets. Each element in the universe of discourse is given a membership degree, reflecting the degree to which the element belongs to the fuzzy set, by the membership functions of the inputs and output, which are represented as fuzzy sets.

The fuzzy inference engine uses a fuzzy operator, such as AND, OR, or MIN, to combine the output fuzzy sets after applying the fuzzy rules to the inputs. The FIS's fuzzy output is the final fuzzy set [32].

The defuzzification module converts the FIS's fuzzy output, which is either a single value or a collection of values, into a crisp output. Defuzzification can be done using a variety of techniques, including the centroid method, the mean of maximum method, and the bisector method.

An example of a fuzzy inference system with 3 inputs and 1 output can be represented by the following equations:

a. Rule 1: IF input1 is A1 AND input2 is B1 AND input3 is C1 THEN output is D1.
b. Rule 2: IF input1 is A2 AND input2 is B2 AND input3 is C2 THEN output is D2 .
c. Rule n: IF input1 is An AND input2 is Bn AND input3 is Cn THEN output is Dn.

Fuzzy output = Fuzzy operator(D1, D2, ..., Dn).

Crisp output = Defuzzification method(Fuzzy output).

Where the fuzzy sets of the inputs and outputs are A1, B1, C1, D1, A2, B2, D2,..., An, Bn, Cn, and Dn, and the fuzzy operator and defuzzification method are those that are used in the FIS. Fuzzy inference systems have been used to model and regulate complex systems as well as carry out classification and prediction tasks in a number of disciplines, including control engineering, data mining, and machine learning. They have a structure similar to that of traditional rule-based systems, but they use fuzzy logic to represent and process uncertain, imprecise, and incomplete information [32].

The fuzzy set equation is a mathematical representation of the membership function of a fuzzy set. The membership function assigns a membership degree to each element in the universe of discourse, indicating the degree to which the element is a part of the fuzzy set. The membership degree is a real number in the range of 0 and 1, where 0 indicates that an element does not belong to the fuzzy set and 1 indicates that an element completely belongs to the fuzzy set [64].

Depending on how the membership function is shaped, the equation for a fuzzy set can be defined in a variety of ways. For example, a triangular fuzzy set can be defined by the equation:

$$mu(x) = max(0, min(1, (x - a) / (b - a))) \tag{3.1}$$

When x is a component of the discourse universe, an is the fuzzy set's left support, b is its right support, and mu(x) is x's membership degree.

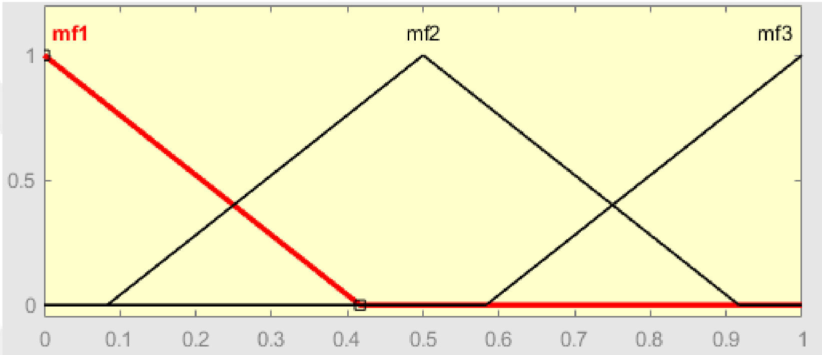

Figure 3.7: Triangular Fuzzy Set.

A trapezoidal fuzzy set can be defined by the equation:

$$mu(x) = max(0, min(1, (x - a) / (b - a), (d - x) / (d - c))) \tag{3.2}$$

where x is a component of the universe of discourse, mu(x) is its membership degree, and a, b, c, d, and mu(x) are the left support, left peak, right peak, right support, and right support, respectively, of the fuzzy set.

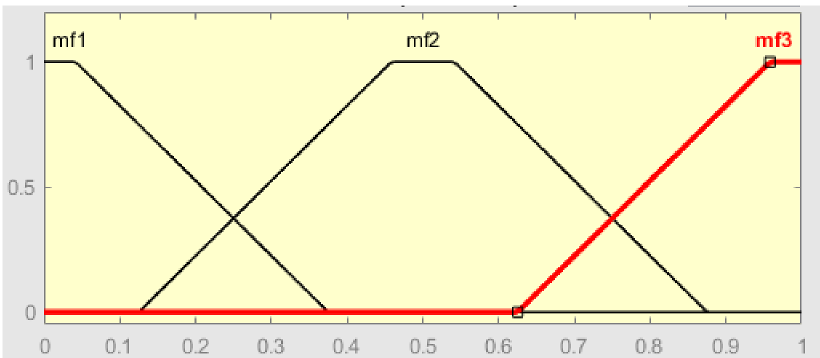

Figure 3.8: Trapezoidal Fuzzy Set.

Other types of fuzzy sets, such as Gaussian fuzzy sets and S-shaped fuzzy sets, can be defined by different equations.

Fuzzy sets are used in fuzzy logic to represent and process uncertain, imprecise, and incomplete information. They allow for the representation of linguistic variables and the use of natural language terms, such as "very," "slightly," and "somewhat," in the rules. Fuzzy sets are used in fuzzy inference systems (FISs) to model and control complex systems, as well as to perform classification and prediction tasks [32].

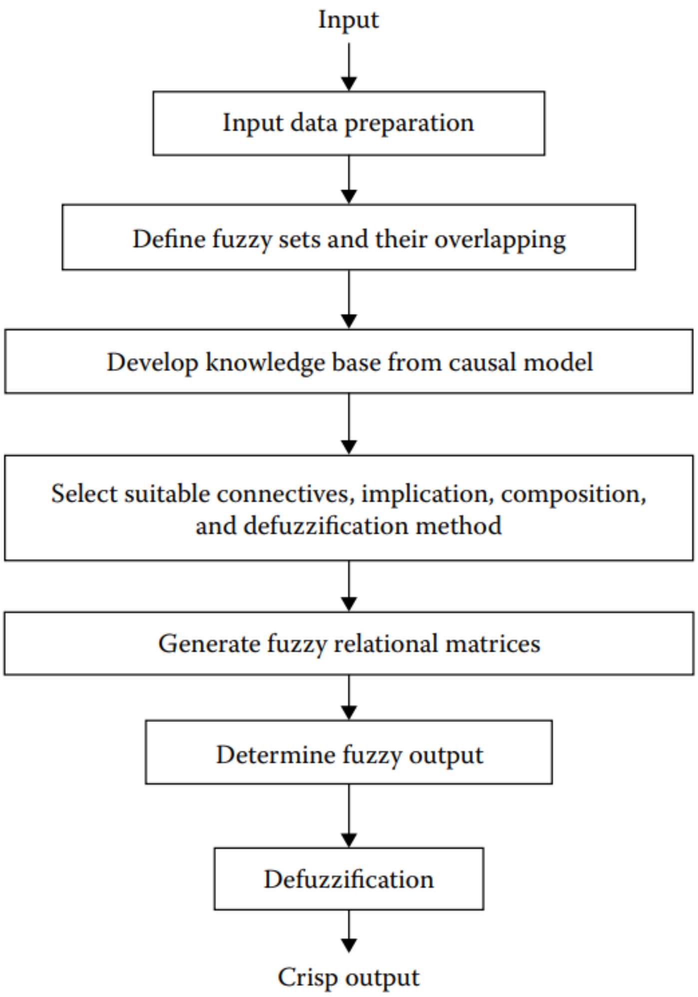

Figure 3.9: Flowchart For The Development Of A Fuzzy Simulator [55].

3.4 ARTIFICIAL NEURAL NETWORKS (ANNs)

Computer programs called artificial neural networks (ANNs) mimic how the human brain interprets and processes information. They are predicated on biological ideas. Instead of learning through programming, ANNs learn by identifying patterns and relationships in data. Instead of being programmed, they learn (or are trained) by experience. An artificial neural network (ANN), which is used to generate the layers that make up the neural structure, is made up of a lot of little components referred to as processing elements (PE) or artificial neurons [35].

The study of artificial neural networks has been a major focus of artificial intelligence (AI) research for many years (ANNs). The structure and activity of the human brain are the basis for the machine learning algorithms known as ANNs. They are composed of networked nodes or neurons that can identify patterns and forecast future events in response to input data [75].

3.4.1 Architecture of ANN’s

Input nodes, hidden nodes, and output nodes make up the foundation of an ANN. The output nodes produce the output depending on the input and the learned patterns after the hidden nodes have processed the input data. Depending on the job at hand, ANNs can be trained using supervised, unsupervised, or reinforcement learning methods.

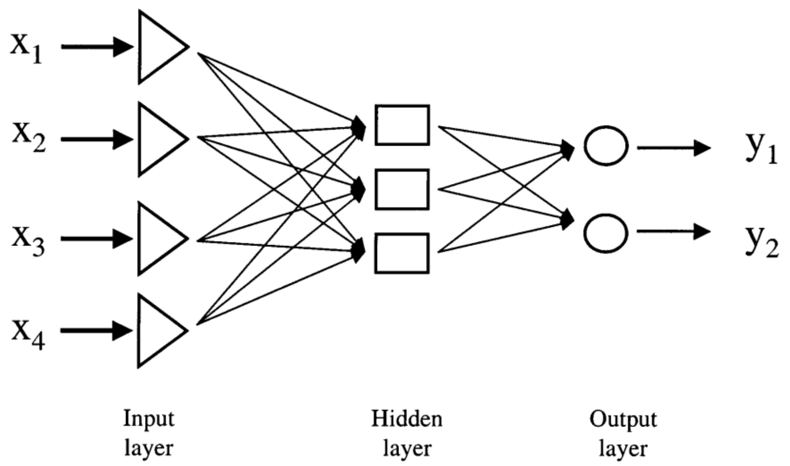

Figure 3.10: Feed-Forward Network [35].

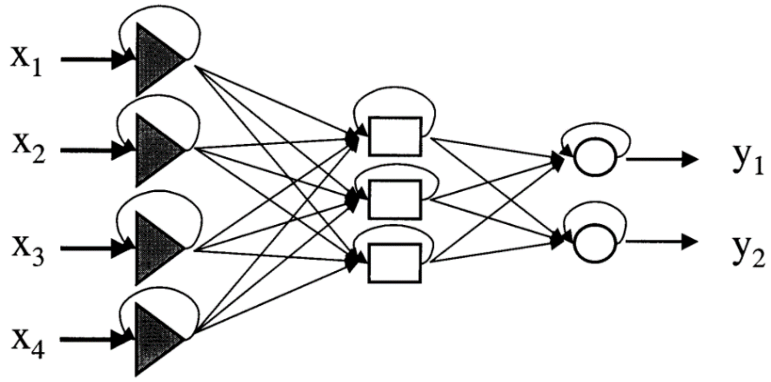

Figure 3.11: Feedback Network [35].

3.4.2 Fields of ANN's

Artificial neural networks (ANNs) have proven effective in a wide range of fields, including speech and image recognition, natural language processing, robotics, and medical analysis for diagnosing illnesses and predicting treatment outcomes. ANNs are characterized by their capacity to learn intricate patterns within massive datasets. Nonetheless, ANNs exhibit some limitations, namely the requirement of abundant data to effectively train the network, the potential for high computational costs when dealing with extensive or complicated tasks, and susceptibility to overfitting, a phenomenon where the network learns to recognize patterns specific to the training data but struggles to generalize to new data [76].

The computing capacity of neural networks is provided by the connections between neurons within a network. Each processing element (PE) contains a weighted input, a single output, and a transfer function [61]. The behavior of a neural network is influenced by its architecture, learning algorithm, and neuronal transfer functions. The properties of the neural network are greatly influenced by the weights, which are changeable parameters. The weighted sum of the inputs is used to compute the activation of the neuron, and the transfer function then generates the final output. The transmission function causes the network to become non-linear. During training, the connections between neurons are adjusted in order to decrease prediction error and achieve the desired level of accuracy [57].

3.5 ADAPTIVE NEURO FUZZY INFERENCE SYSTEM (ANFIS)

Fuzzy inference systems (FIS) that integrate fuzzy logic and artificial neural networks (ANNs) are known as adaptive neuro-fuzzy inference systems (ANFIS). ANFISs are utilized to conduct classification and prediction tasks, as well as to model and regulate complex systems [44]. They have been utilized in a number of domains, including machine learning, data mining, and control engineering [36]. ANFISs are made up of a fuzzy rule base, a fuzzy inference engine, and a defuzzification module, similar to standard FISs. The ANFIS's parameters, such as its membership functions and fuzzy rules, can, however, be changed as the learning process progresses. The gradient descent algorithm is used by ANFISs to optimize the parameters and reduce the difference between the desired and predicted results. Compared to conventional FISs and ANNs, ANFISs have a number of advantages. They can first deal with data that is ambiguous and imprecise, as well as intricate interactions between variables. Second, they can learn from examples and adapt to changes in the system. Third, they are flexible and can be easily modified or updated with new rules and knowledge. However, ANFISs also have some limitations. For them to accurately simulate a complicated system, a large number of rules and a big number of training examples may be necessary [37]. They might also be sensitive to how the parameters are initialized and the learning rate. As a result, ANFISs are an effective and practical tool for modeling and managing complex systems as well as carrying out classification and prediction tasks. They are able to deal with the data's ambiguity and imprecision, draw lessons from past experiences, and adjust to system changes. However, they might need a lot of rules and training examples, and they might be sensitive to how the parameters are initialized and how quickly they learn. There are five layers in the ANFIS system. The input layer is the top layer, where the system receives input data. The input data is transformed into fuzzy sets using membership functions in the second layer, which is called the membership function layer. The fuzzy inference layer, which makes decisions by applying fuzzy rules to fuzzy sets, is the third layer. The outputs of the fuzzy inference layer are normalized at the fourth layer, which is the normalization layer. The output layer, which is the fifth layer, is where the choice is made in the end [46].

3.5.1 Anfis Rules

The knowledge and reasoning required to make decisions based on input data are provided by rules, which play a crucial role in ANFIS. Rules determine the link between input and output variables in addition to provide a way for domain experts to convey their knowledge and experience. The output accuracy of ANFIS may be impacted by the quantity and complexity of its rules. Too few rules may result in an oversimplified model that does not capture the nuances of the input data, while too many rules may result in overfitting and decreased generalization. Therefore, it is important to carefully select and design the rules in ANFIS to achieve the desired level of accuracy and generalization.

In a study by Singh et al. [52], an ANFIS model was created to predict the groundwater level in a water-stressed area. The accuracy of the model was evaluated using statistical metrics including root mean square error (RMSE) and mean absolute error (MAE). The study found a trade-off between accuracy and complexity, with the accuracy of the ANFIS model increasing as the number of rules grew. They suggested selecting the optimal number of rules based on the features of the data and the desired level of accuracy.

ANFIS was employed in a different investigation by Das et al. [53] to forecast the compressive strength of high-performance concrete. The study assessed how the number of rules and other input factors affected the ANFIS model's accuracy. The findings indicated that adding more rules increased the model's accuracy, but there was a point beyond which doing so had no further beneficial effects. Based on the features of the data and the desired level of accuracy, the study suggested choosing the ideal number of rules.

The design and wording of the rules are equally important to choosing the right amount of rules in ANFIS. ANFIS was utilized in a study by Fattahi et al. [54] to forecast the stability of a slope in an area vulnerable to landslides. The study assessed the impact of various rule formulations on the ANFIS model's accuracy. The findings demonstrated that, in comparison to utilizing solely triangle or

Gaussian membership functions, a mix of triangular and Gaussian membership functions enhanced the model's accuracy. Based on the features of the data and the desired level of accuracy, the study suggested choosing the best mix of membership functions.

Because they offer the knowledge and logic required to make decisions based on incoming data, rules play a crucial role in ANFIS. The accuracy and generalizability of the ANFIS model can be impacted by the quantity and complexity of the rules. The rules in ANFIS should be carefully chosen and created in order to achieve the necessary level of generalization and accuracy. The desired level of accuracy and the features of the data determine the ideal number and formulation of the rules. ANFIS is a powerful tool for modeling complex systems with uncertain or incomplete information, and the proper selection and design of rules are essential for its success.

3.5.2 Back Propagation Algorithm vs. Hybrid Algorithms

Popular neural network algorithm backpropagation has been applied to a number of applications, including the adaptive neuro-fuzzy inference system (ANFIS). In order to produce judgments and predictions, ANFIS is a form of hybrid system that combines the advantages of neural networks and fuzzy logic [48].

While backpropagation has been successful in many applications, it has some limitations. Its need for a substantial amount of training data is one of its drawbacks. This can be a challenge in applications where data is scarce or expensive to obtain. Another limitation is that backpropagation can get stuck in local minima, which can lead to suboptimal solutions. Researchers have developed techniques such as dropout and batch normalization to mitigate these limitations [49].

The neural network's weights and biases are trained using the back-propagation algorithm. The fuzzy inference system (FIS) that is utilized to make judgments in the ANFIS system is parameterized using the back-propagation process. Fuzzy logic and neural networks are combined by the ANFIS system to make judgments based on input data. The input data are initially transformed into fuzzy sets by the system using membership functions. Fuzzy rules are then used to combine the membership functions to reach a conclusion. The back-propagation algorithm is used to modify the fuzzy rules' weights [46]. Hybrid algorithms, on the other hand, combine many optimization strategies in order to get beyond the drawbacks of individual algorithms. ANFIS models can be trained more effectively than single algorithms by using hybrid methods. In order to train ANFIS models, hybrid techniques such as genetic algorithms, particle swarm optimization, ant colony optimization, and differential evolution are sometimes utilized.

The task and dataset being used determine how well the back-propagation algorithm and hybrid algorithms perform when training ANFIS models. The back-propagation algorithm has drawbacks, including a propensity for local minima and slow convergence in deep networks, despite being widely used and straightforward to implement. To get around these restrictions and boost the precision and convergence rate of ANFIS models, hybrid algorithms can be used. Therefore, a hybrid algorithm should be selected based on the features of the task and dataset being used [71].

3.6 EXTRA-TREES REGRESSOR

Extra trees regressor is a powerful tool for regression tasks, which are problems that involve predicting continuous or ordered values. It is an ensemble learning method, which means that it combines the predictions of multiple models to obtain a better performance [38]. Extra trees regressor is a variant of the random forest algorithm, which is a popular method for classification and regression. Extra trees regressor is based on decision trees, which are models that make predictions by learning a set of rules from the data. Using splits that maximize a criterion, such as the information gain or, decision trees are trained by segmenting the input space into areas based on the values of the input features. A decision produced by the tree corresponds to each region, and each decision has a root node, an intermediate node, and a leaf node. The leaf nodes contain the predicted outputs, which are the averages or modes of the outputs in the training data that belong to the region [39].

Extra-trees regressor extends decision trees by building multiple decision trees and combining their predictions. It creates a diverse set of decision trees by sampling the input space and the output space in different ways. It bootstraps the training data to sample the output space, which is a method of sampling with replacement, and samples the input space by picking a random subset of the input characteristics at each split. The bootstrapped samples are used to train each decision tree, and the samples are different for each tree. Depending on the objective, the extra-trees regressor either averages or votes the predictions from the decision trees. It can handle missing values and can handle multiclass and multilabel tasks, by using the one-versus-rest or the one-versus-one approaches. It can also handle imbalanced data, by using sampling or weighting techniques.

Extra-trees regressor has several advantages over other methods. It is simple to implement, it is fast to train and to predict and robust to overfitting, it is accurate, stable, and interpretable. It can handle high-dimensional and complex data, and it can handle a large number of input features [39]. Nevertheless, extra-trees regressor has some limitations. It is sensitive to noise and outliers, it is sensitive to the sampling method and the sampling parameters, and it is sensitive to the criterion and the tree parameters. As a result, it might not be as accurate as other techniques like gradient boosting or support vector machines. It might also suffer from bias and variance trade-offs.

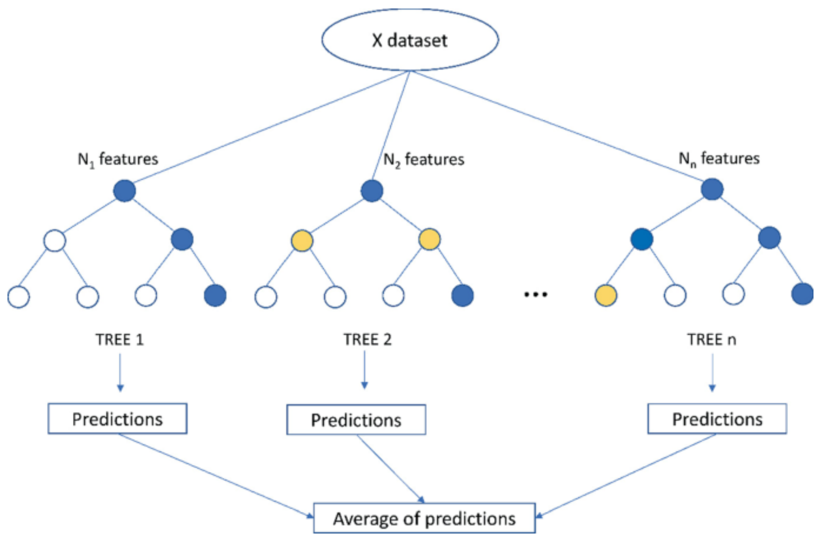

Figure 3.12: Extra-Trees Regressor [47].

4. PROPOSED METHOD

4.1 INTRODUCTION

Since climate change has become the most popular topic among researchers for its maximum importance, in this suggested study, we suggest using an ANFIS model as a means of predicting the amount of CO2 emissions from vehicles. To train the model, a set of vehicle characteristics and related CO2 emissions data will be used. The model's input variables will contain things like the engine's size, number of cylinders, and the fuel consumption. The anticipated CO2 emissions will be the output variable.

The ANFIS model will be trained using the supervised learning approach so that it can adjust to the quirks of the data and produce accurate predictions. Since it can deal with input variable uncertainty, the model will be more resistant to real-world situations.

The results of this study will be validated by comparing the performance of the ANFIS model using the dataset to the same model using the improved dataset. We anticipate that the ANFIS model will achieve a high degree of accuracy and be able to offer insightful information about how vehicle attributes and CO2 emissions relate to one another.

4.2 SYSTEM OUTLINE

The main aim of the proposed study will be achieved through a methodical approach that can be divided into four parts.

a. Editing the datasets by neglecting the unnecessary columns.

b. Building the ANFIS model and train it and validate results.

c. Enhancing the dataset by applying extra trees regressor algorithm and generate a new dataset.

d. Train the model with the new generated dataset and validate results.

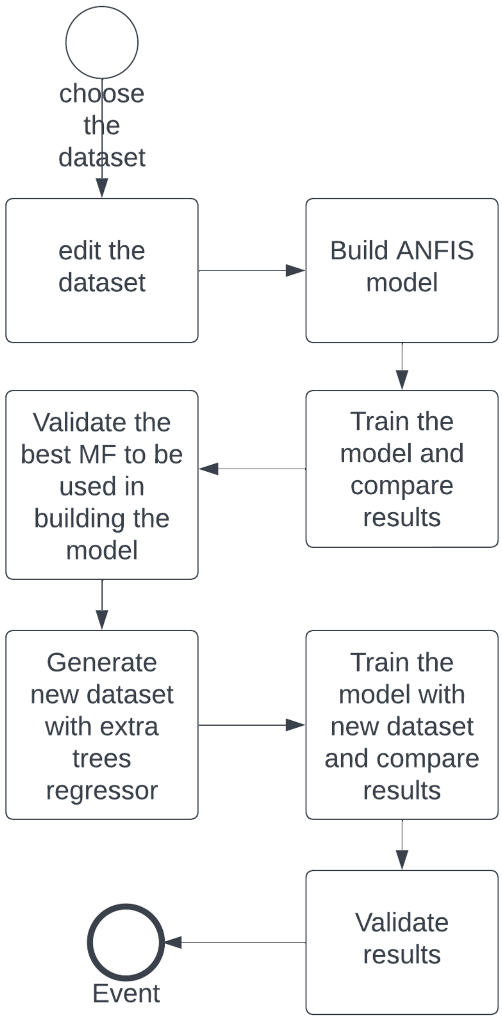

Figure 4.1: System Outline.

4.2.1 Dataset Used

The dataset for this study is a comprehensive collection of data that is relevant to the research question being investigated. The dataset has been carefully curated and includes a wide range of variables that are essential for addressing the research objectives. The dataset used belongs to the Canadian governments "Natural resources of Canada" [56] to ensure its validity and reliability. The proposed dataset for this study is a valuable resource that will enable the researchers to conduct a thorough analysis and draw meaningful conclusions. One of the key strengths of the proposed dataset for this study is its diversity. The large sample size of the proposed dataset for this study is another benefit. With thousands of observations. A thorough analysis of the research issue is possible thanks to the large variety of variables included in the suggested dataset for this study. The variables include details like engines sizes and number of cylinders for a huge variety of vehicles. It also includes an average of fuel consumption for both inside cities and on highways. The proposed dataset for this study is a valuable resource that will enable the researchers to conduct a thorough analysis and draw meaningful conclusions. With its diversity, large sample size, and wide range of variables, the dataset is well-suited for addressing the research question and achieving the research objectives.

Table 4.1: Dataset Used For The Study.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Make	Model	Vehicle Class	Engine Size	Cylinders	Transmissi	Fuel Type	Fuel Consu	Fuel Consu	Fuel Consu	Fuel Consu	CO2 Emissions(g/km)	
2	ACURA	ILX	COMPACT	2	4	AS5	Z	9.9	6.7	8.5	33	196	
3	ACURA	ILX	COMPACT	2.4	4	M6	Z	11.2	7.7	9.6	29	221	
4	ACURA	ILX HYBRID	COMPACT	1.5	4	AV7	Z	6	5.8	5.9	48	136	
5	ACURA	MDX 4WD	SUV - SMALL	3.5	6	AS6	Z	12.7	9.1	11.1	25	255	
6	ACURA	RDX AWD	SUV - SMALL	3.5	6	AS6	Z	12.1	8.7	10.6	27	244	
7	ACURA	RLX	MID-SIZE	3.5	6	AS6	Z	11.9	7.7	10	28	230	
8	ACURA	TL	MID-SIZE	3.5	6	AS6	Z	11.8	8.1	10.1	28	232	
9	ACURA	TL AWD	MID-SIZE	3.7	6	AS6	Z	12.8	9	11.1	25	255	
10	ACURA	TL AWD	MID-SIZE	3.7	6	M6	Z	13.4	9.5	11.6	24	267	
11	ACURA	TSX	COMPACT	2.4	4	AS5	Z	10.6	7.5	9.2	31	212	
12	ACURA	TSX	COMPACT	2.4	4	M6	Z	11.2	8.1	9.8	29	225	
13	ACURA	TSX	COMPACT	3.5	6	AS5	Z	12.1	8.3	10.4	27	239	
14	ALFA ROMEO	4C	TWO-SEATER	1.8	4	AM6	Z	9.7	6.9	8.4	34	193	
15	ASTON MARTIN	DB9	MINICOMPACT	5.9	12	A6	Z	18	12.6	15.6	18	359	
16	ASTON MARTIN	RAPIDE	SUBCOMPACT	5.9	12	A6	Z	18	12.6	15.6	18	359	
17	ASTON MARTIN	V8 VANTA	TWO-SEATER	4.7	8	AM7	Z	17.4	11.3	14.7	19	338	
18	ASTON MARTIN	V8 VANTA	TWO-SEATER	4.7	8	M6	Z	18.1	12.2	15.4	18	354	
19	ASTON MARTIN	V8 VANTA	TWO-SEATER	4.7	8	AM7	Z	17.4	11.3	14.7	19	338	
20	ASTON MARTIN	V8 VANTA	TWO-SEATER	4.7	8	M6	Z	18.1	12.2	15.4	18	354	
21	ASTON MARTIN	VANQUISH	MINICOMPACT	5.9	12	A6	Z	18	12.6	15.6	18	359	
22	AUDI	A4	COMPACT	2	4	AV8	Z	9.9	7.4	8.8	32	202	
23	AUDI	A4 QUATT	COMPACT	2	4	AS8	Z	11.5	8.1	10	28	230	
24	AUDI	A4 QUATT	COMPACT	2	4	M6	Z	10.8	7.5	9.3	30	214	
25	AUDI	A5 CABRIC	SUBCOMPACT	2	4	AS8	Z	11.5	8.1	10	28	230	
26	AUDI	A5 QUATT	SUBCOMPACT	2	4	AS8	Z	11.5	8.1	10	28	230	
27	AUDI	A5 QUATT	SUBCOMPACT	2	4	M6	Z	10.8	7.5	9.3	30	214	

4.2.2 Proposed Dataset

The proposed dataset was subjected to modifications in order to be eligible for the study. Modifications included neglecting some of the columns that were not considered as essential. For example, many brand makes have the same engine size, so it was neglected, model, vehicle class and fuel type were also neglected for the same purpose.

Table 4.2: Proposed Dataset.

	A	B	C	D
1	Engine Size(L)	Cylinders	Fuel Consumption Comb (L/100 km)	CO2 Emissions(g/km)
2	2	4	8.5	196
3	2.4	4	9.6	221
4	1.5	4	5.9	136
5	3.5	6	11.1	255
6	3.5	6	10.6	244
7	3.5	6	10	230
8	3.5	6	10.1	232
9	3.7	6	11.1	255
10	3.7	6	11.6	267
11	2.4	4	9.2	212
12	2.4	4	9.8	225
13	3.5	6	10.4	239
14	1.8	4	8.4	193
15	5.9	12	15.6	359
16	5.9	12	15.6	359
17	4.7	8	14.7	338
18	4.7	8	15.4	354
19	4.7	8	14.7	338
20	4.7	8	15.4	354
21	5.9	12	15.6	359
22	2	4	8.8	202
23	2	4	10	230
24	2	4	9.3	214

4.3 ANFIS MODEL

We created the ANFIS model using Matlab R2022, using "Engine size," "Number of cylinders," and "fuel consumption" as input parameters and "emissions" as an output parameter.

The efficiency of the Adaptive Neuro-Fuzzy Inference System (ANFIS) model can be significantly impacted by the choice of a membership function. The distinctive properties of the dataset and the kind of problem being addressed determine the best membership function to use.

The membership functions (MFs) for each input variable should be specified. These are used to describe how the input variables should be translated into fuzzy sets, which may then be utilized to draw fuzzy conclusions. There are different ways to define MFs, such as by using Gaussian functions or trapezoidal functions.

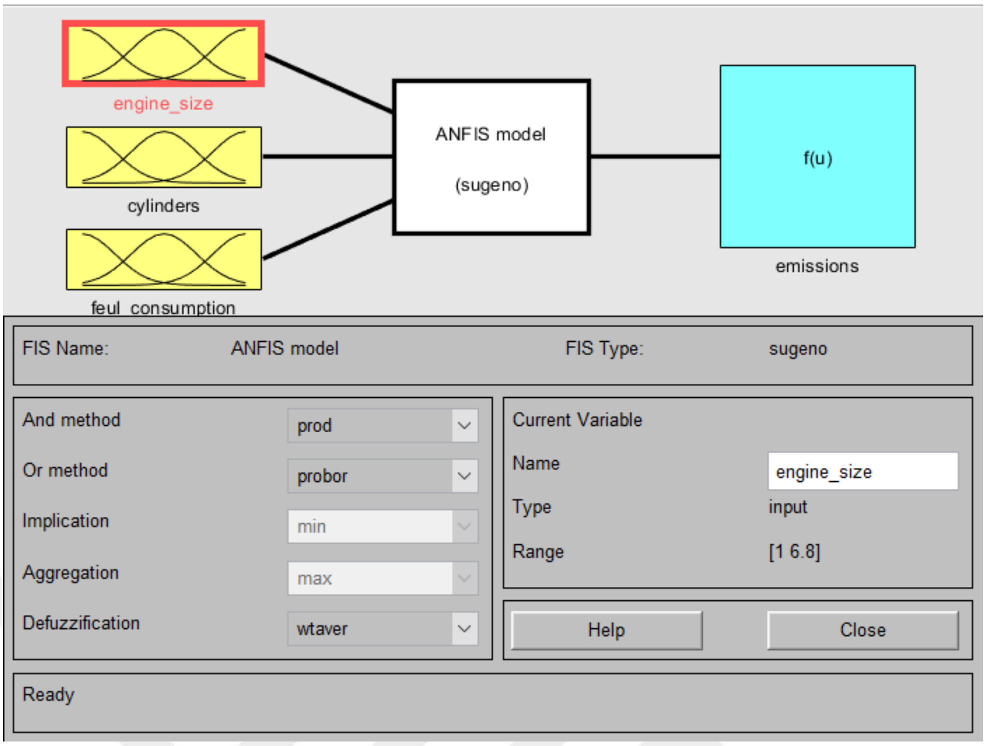

Figure 4.2: ANFIS Model.

4.3.1 Anfis Model Training

An Adaptive Neuro-Fuzzy Inference System (ANFIS) model is trained by defining the input and output data sets first, initializing the ANFIS model with random parameter values from the dataset, and then changing the ANFIS model's parameter values using a learning algorithm, like back-propagation, to lessen the discrepancy between the model's output and the desired output. The model's benefits for instruction include:

a. Handle nonlinearity: ANFIS models are useful in applications where conventional linear models fail because they can handle nonlinear relationships between input and output variables.

b. Handling uncertainty: ANFIS models can handle uncertain or inaccurate data thanks to fuzzy logic, which makes them ideal for issues with missing or noisy data.

c. Taking into account numerous inputs: ANFIS models can account for a wide range of input variables, which is advantageous in situations where the relationships between the input and output variables are complex.

d. High-dimensional issues: ANFIS models can handle high-dimensional issues, they are advantageous for issues with numerous input variables. After loading the data into the workspace of Matlab, we will generate the FIS model.

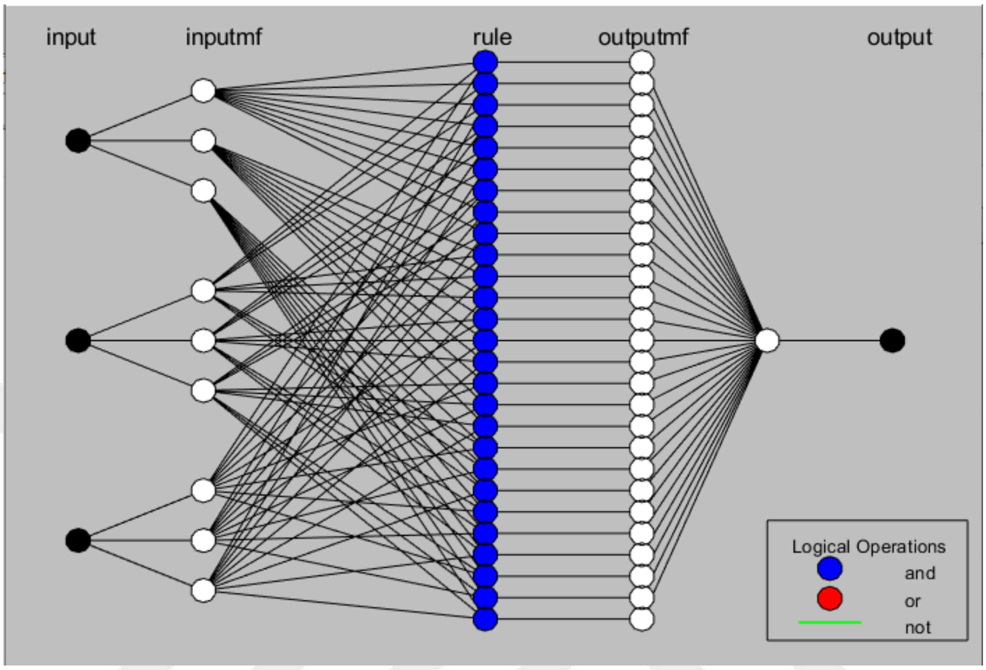

Figure 4.3: ANFIS Model Structure.

The four primary structural components of ANFIS are the fuzzification module, the rule-base, the inference engine, and the defuzzification module [40]. The fuzzification module employs a membership function to transform the crisp values of each input variable into fuzzy sets. This membership function determines the degree to which the input value is a member of a particular fuzzy set. The relationship between the input and output variables is represented by the rule-base, which is a collection of ambiguous if-then rules. Each rule consists of a collection of antecedents (conditions) and a consequence (action). The antecedents are drawn from the fuzzy sets generated by the fuzzification module, whilst the consequent is represented by a fuzzy set that corresponds to the output variable.

4.3.2 Membership Functions

Choosing the optimum membership function is a crucial stage in the training of an Adaptive Neuro-Fuzzy Inference System (ANFIS) model since it has a big impact on the model's performance. Different membership function types are useful for diverse sorts of data and issues due to their unique characteristics. The level of membership of a given input value to a certain fuzzy set is defined by a membership function. [41].

Depending on the membership function chosen, the ANFIS model's performance may be significantly affected. Each type of membership function has its own advantages and disadvantages. The most straightforward and widely used membership functions are triangular and trapezoidal. They are suitable for issues where the input variables have clearly defined ranges and are simple to implement.

When input data is continuous and regularly distributed, more complicated Gaussian membership functions are frequently used. Compared to triangle and trapezoidal functions, gaussian membership functions are more adaptable and can better represent the shape of the data.

Within the proposed study, we started the process by dividing the dataset to 70% for training, 30% for testing the model. [5168*4] matrix for training and [2217*4] matrix for testing and validating the model was uploaded. We generated the FIS using multiple membership functions to achieve the best results. The membership functions that were tested are listed as shown in Fig (4.4, 4.5) respectively.

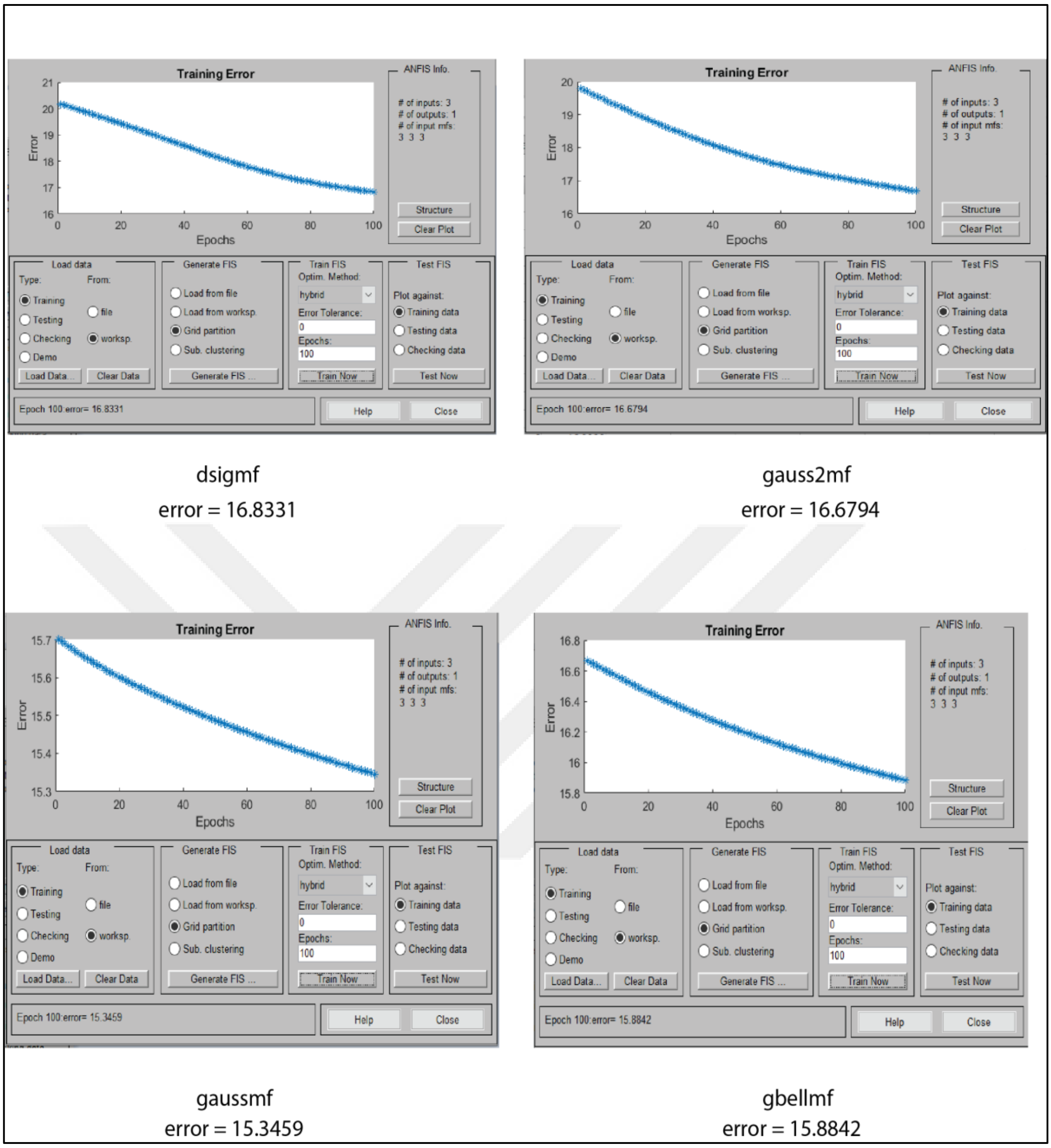

Figure 4.4: Membership Functions (Dsigmf, Gauss2mf, Gaussmf, Gbellmf).

Figure 4.5: Membership Functions (Pimf, Psigmf, Trapmf, Trimf).

In this study, the outcomes of training using various membership functions over 100 epochs were examined. The "gaussmf" has been noted to have the best error results, so it will be taken into consideration when building the model.

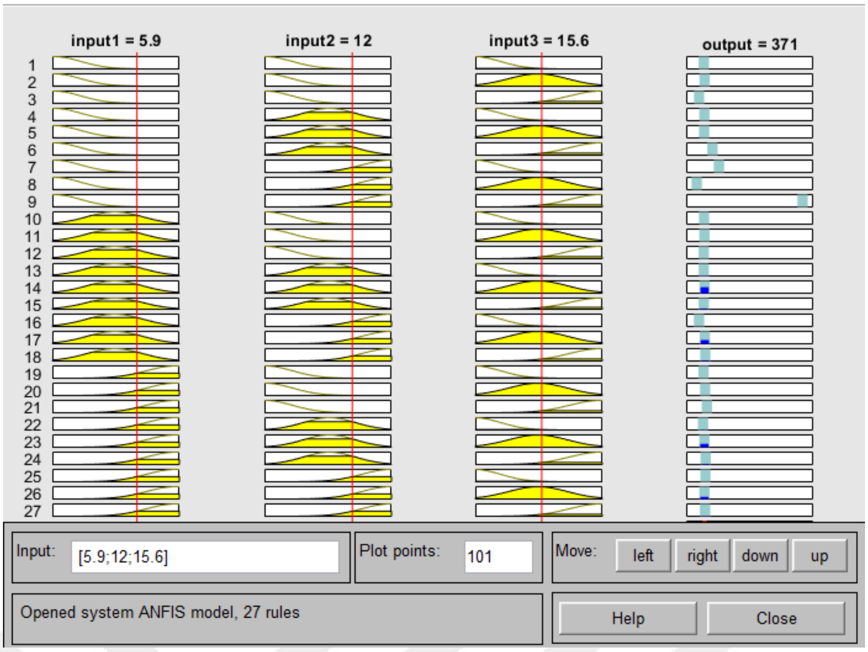

Figure 4.6: ANFIS Model Rule Viewer.

The rule viewer can be used to gain a deeper understanding of the fundamental relationship between the input and output variables. The ANFIS model's functionality and any potential weaknesses can be understood and found using the Rule Viewer. It can facilitate model modifications and help with problem identification.

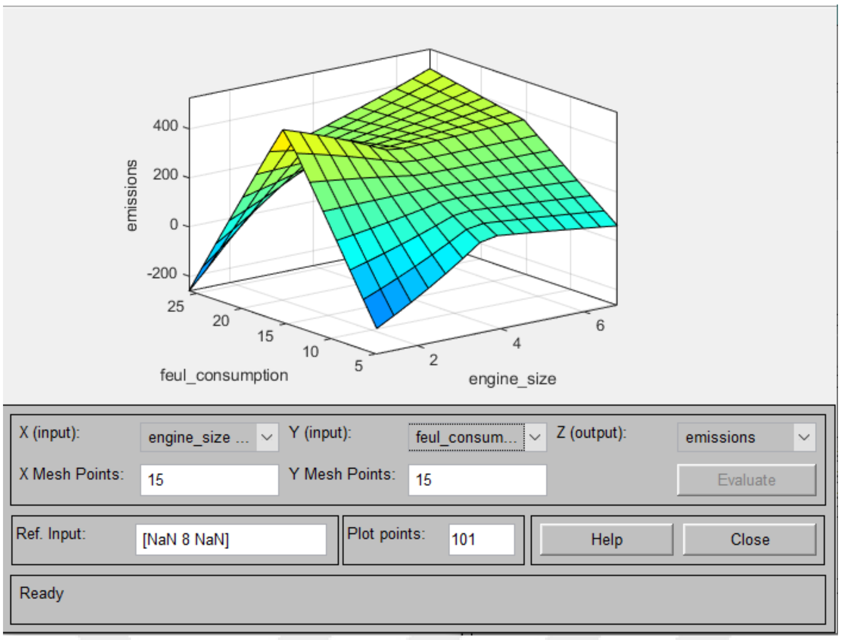

Figure 4.7: ANFIS Model Surface Viewer.

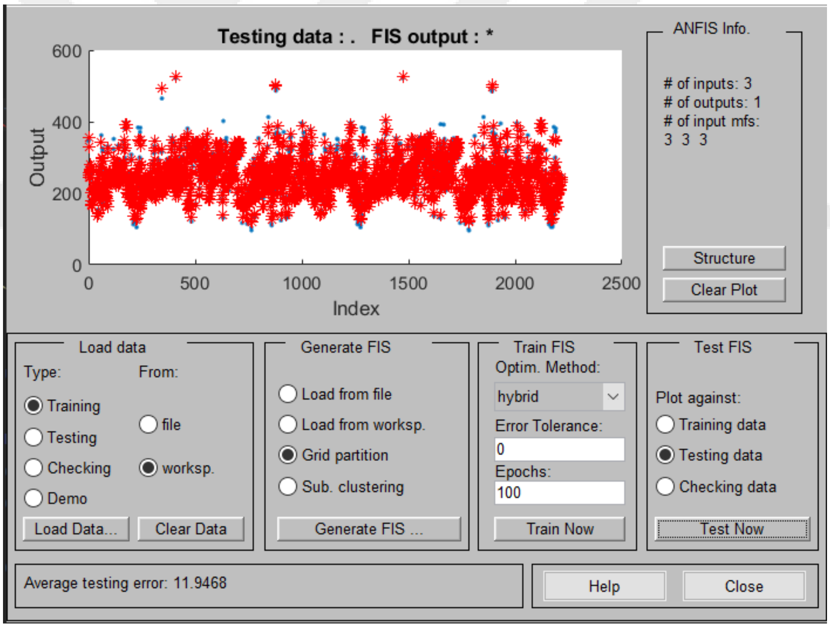

Figure 4.8: ANFIS Model Testing Error Rate.

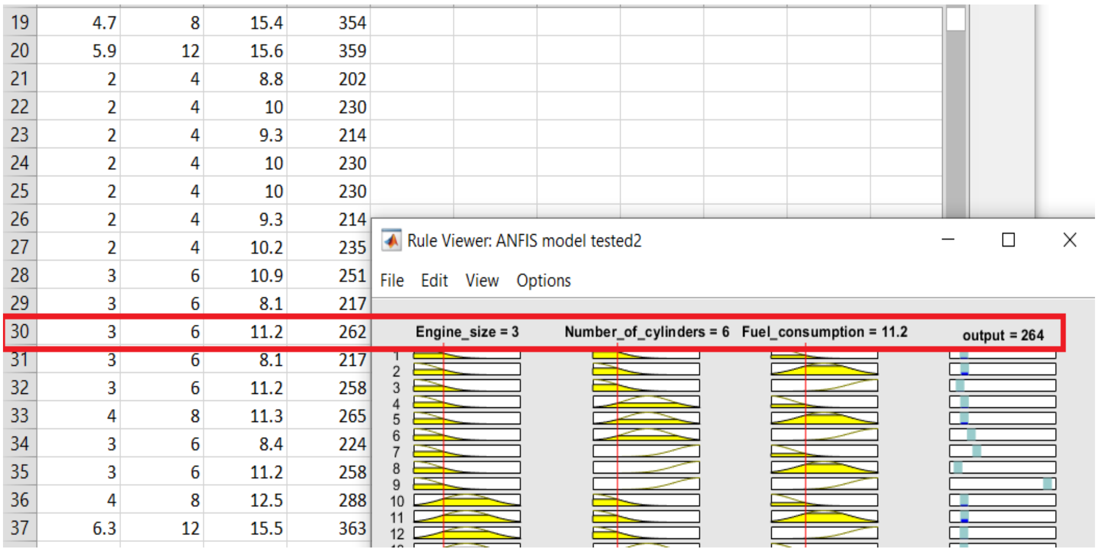

Figure 4.9: ANFIS Model Accuracy Rate (Outputs Are Measured In Grams).

Within this model we will be able to predict the emissions form any kind of vehicles with a testing error rate of (11.9468). The surfaces are used to describe information about objects which is stored in training data [42].

4.3.3 Enhancing The Dataset

For more accurate results, an optimization to the training procedure will be conducted to generate another dataset by applying extra trees regressor algorithm on the current dataset. The method may be employed as a tool for refining the ANFIS model's parameters.

The previous dataset consisted of (7384*4), the generated dataset will be up to (56897*4) which is supposed to be more efficient for training the model.

4.3.4 Re-train The ANFIS Model

The same training procedure was conducted using the same membership functions for validating the membership function with the least error rate. The "gaussmf" showed the best result as shown in fig 4.10, 4.11 respectively.

Figure 4.10: Membership Functions For ANFIS Model After Retraining.

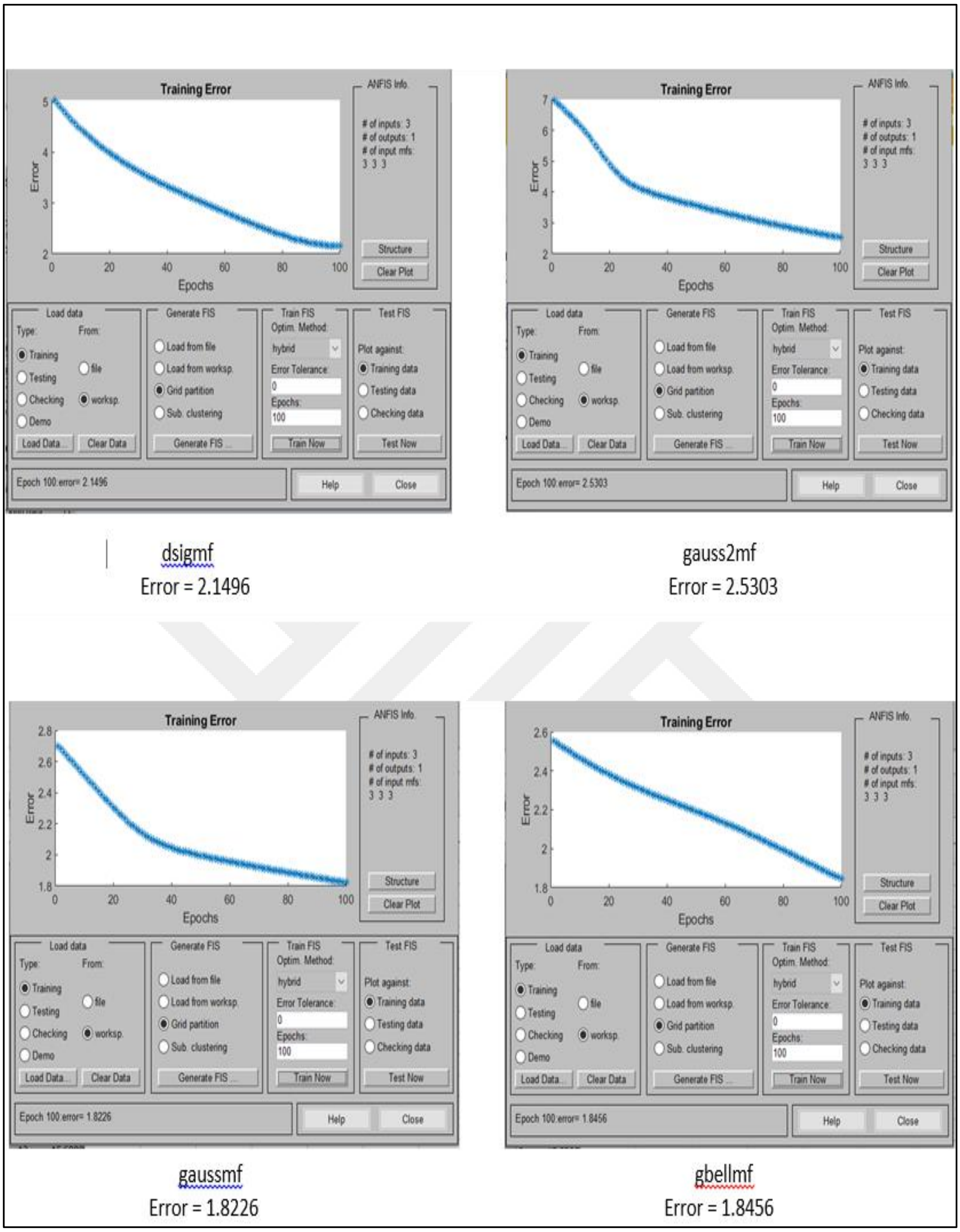

Figure 4.11: Membership functions for ANFIS model after retraining.

As can be seen in fig. 4.12 below, this step of the study's methodology clearly showed that the (gaussmf) had once again achieved the best results in terms of the accuracy for predicting the amount of the output, with an average testing error rate for training of 1.8226 and an average testing error rate for testing of 1.767.

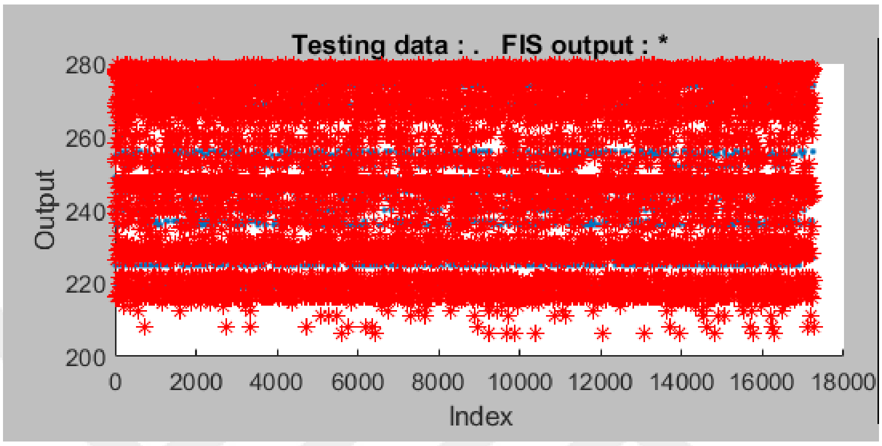

Figure 4.12: Average Testing Error Rate = 1.767 For ANFIS Model After Retraining.

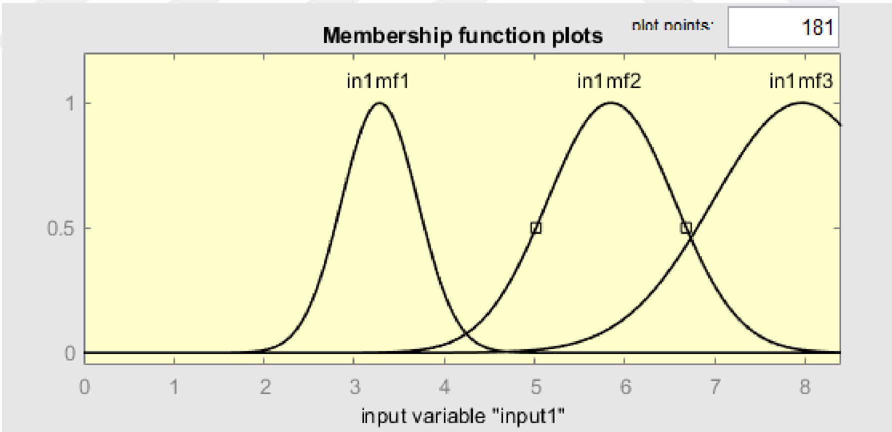

Figure 4.13: Engine Size Membership Function.

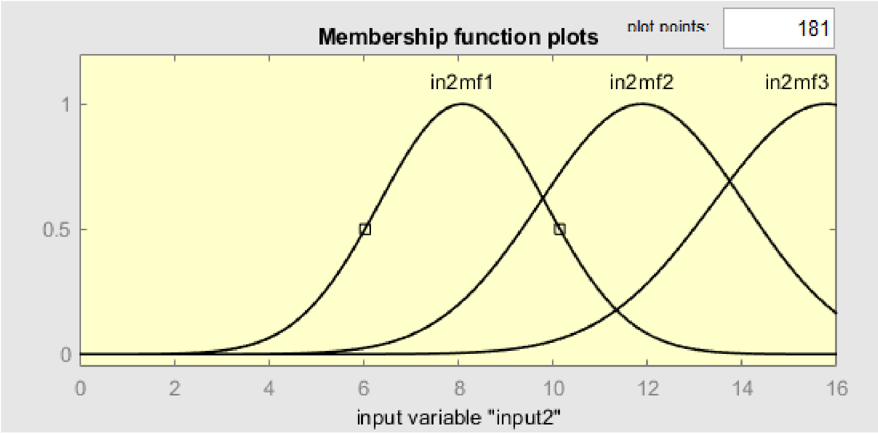

Figure 4.14: Number of Cylinders (3-16 Cylinders) Membership Function.

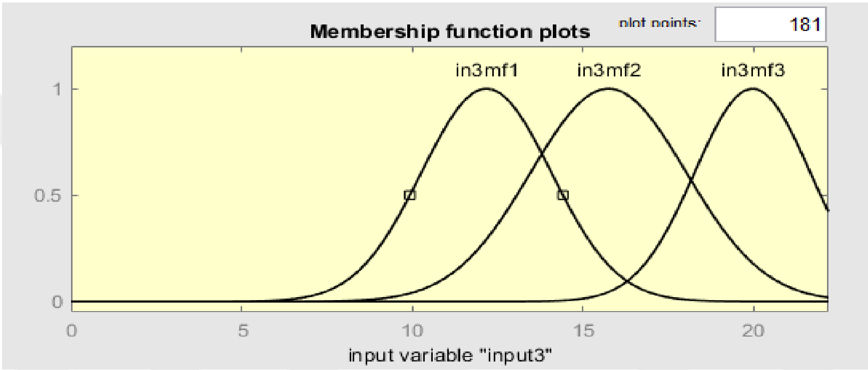

Figure 4.15: Fuel Consumption (Liter/100 Km) Membership Function.

Once the model is built, a bit of tuning is necessary for the membership functions and this may cause increasing the average error rate as shown in fig 4.16.

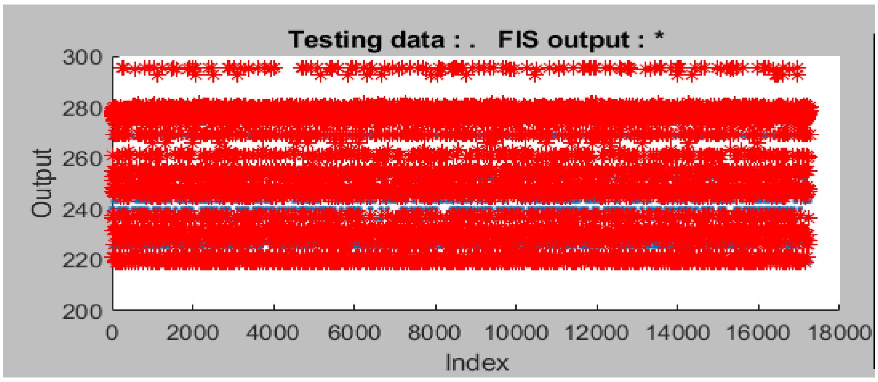

Figure 4.16: Average Error Rate (4.2801) For ANFIS Model After Tuning The Membership Functions.

The amount and complexity of the rules in ANFIS can have an impact on the accuracy of the system's output. Too few rules could lead to an oversimplified model that misses the subtleties of the input data, whereas too many rules could overfit the model and reduce generalization. To achieve the desired level of accuracy and generalization, it is crucial to carefully choose and design the ANFIS rules. The below table shows the rules that was generated by the Fuzzy Inference System (FIS).

Table 4.3: rules for the design.

Rules	Input 1 Engine size	Input 2 Number of cylinders	Input 3 Fuel consumption	Output Emissions
1	In1mf1	In2mf1	In3mf1	Out1mf1
2	In1mf1	In2mf1	In3mf2	Out1mf2
3	In1mf1	In2mf1	In3mf3	Out1mf3
4	In1mf1	In2mf2	In3mf1	Out1mf4
5	In1mf1	In2mf2	In3mf2	Out1mf5
6	In1mf1	In2mf2	In3mf3	Out1mf6
7	In1mf1	In2mf3	In3mf1	Out1mf7
8	In1mf1	In2mf3	In3mf2	Out1mf8
9	In1mf1	In2mf3	In3mf3	Out1mf9
10	In1mf2	In2mf1	In3mf1	Out1mf10
11	In1mf2	In2mf1	In3mf2	Out1mf11
12	In1mf2	In2mf1	In3mf3	Out1mf12
13	In1mf2	In2mf2	In3mf1	Out1mf13
14	In1mf2	In2mf2	In3mf2	Out1mf14
15	In1mf2	In2mf2	In3mf3	Out1mf15
16	In1mf2	In2mf3	In3mf1	Out1mf16
17	In1mf2	In2mf3	In3mf2	Out1mf17
18	In1mf2	In2mf3	In3mf3	Out1mf18
19	In1mf3	In2mf1	In3mf1	Out1mf19
20	In1mf3	In2mf1	In3mf2	Out1mf20
21	In1mf3	In2mf1	In3mf3	Out1mf21
22	In1mf3	In2mf2	In3mf1	Out1mf22
23	In1mf3	In2mf2	In3mf2	Out1mf23
24	In1mf3	In2mf2	In3mf3	Out1mf24
25	In1mf3	In2mf3	In3mf1	Out1mf25
26	In1mf3	In2mf3	In3mf2	Out1mf26
27	In1mf3	In2mf3	In3mf3	Out1mf27

4.4 SIMULATION RESULTS

The "gaussmf" function was found to have the highest accuracy, with an error rate of 15.3459 percent, based on the results of the model's simulations. Nonetheless, this level of inaccuracy is inadequate for rendering significant decisions. To rectify this matter, a proposal was put forward to adjust the dataset utilizing the Extra-trees regressor to create a new dataset that is approximately 7 times larger than the original dataset. Although this method prolongs the time needed for testing and training, it is hoped that it will improve the model's accuracy.

The procedure of constructing the model with various membership functions was re-executed using the novel dataset, and yet again, the "gaussmf" function manifested the utmost precision with an error rate of 1.8226%. Through this achievement of reducing the error rate from 15% to 1.8226%, our suggested model was able to substantiate its precision and efficacy in contrast to the initial, unaltered dataset.

Our main aim in conducting this research was to create a machine learning model that is both efficient and precise in its ability to anticipate the characteristics and emissions of vehicles with minimal margin of error. By means of adapting the dataset using the Extra-trees regressor, we were able to successfully achieve this objective, and furthermore, we substantiated the efficiency of our proposed model.

In essence, our research emphasizes the significance of data preprocessing in attaining elevated accuracy rates in machine learning models. The use of a more extensive dataset that was generated by the Extra-trees regressor enabled us to achieve notably improved precision levels in comparison to the original dataset. The implications of these findings are extendable to other fields where accurate forecasting is imperative for effective decision-making.

5. CONCLUSIONS AND FUTURE WORK

5.1 CONCLUSION

The use of the ANFIS model, one of the machine learning technologies, is shown in this study to be a practical option for predicting the amount of vehicle emissions and to produce accurate results, as a conclusion. The adaptive learning capabilities of the ANFIS model set it apart from traditional fuzzy inference systems and contribute to its credibility as a real-world problem-solving tool. The model accurately depicts how the input variables and the output variable relate to one another. In general, ANFIS provides a versatile and effective method for modeling dynamic systems, and its ability to manage a large number of inputs and outputs makes it a highly valued tool in a variety of fields.

The findings from the previous chapter show that one of the most important variables influencing the results is the choice of the appropriate membership function.

The ANFIS model's high accuracy demonstrates its potential for accurately forecasting CO_2 emissions from vehicles. The ability of the model to handle non-linear relationships and uncertainty in the data makes it well-suited for this type of problem. Furthermore, the fact that the model considers multiple inputs in its predictions can provide a more complete and accurate representation of the relationship between vehicle characteristics and emissions. These findings emphasize the significance of applying cutting-edge modeling methods, like ANFIS, to tackle the urgent problems of lowering emissions in the transportation sector and reducing the effects of climate change.

5.2 FUTURE WORK

The ANFIS model developed to predict CO_2 emissions from vehicles is a promising foundation for future investigations in emissions prediction. Through the adaptation of this model for diverse sectors, researchers can create precise prediction models that facilitate the optimization of emission reduction strategies for various industries. Future research should concentrate on two areas to improve the accuracy of such models: the incorporation of unique input parameters specific to various industries and model refinement. Accurate prediction models are becoming more and more crucial across a range of industries, especially in light of the global concern over reducing greenhouse gas emissions.

The proposed model can be used to make comparisons with different datasets that belongs to other countries with different standards.

As the world struggles to deal with the threat of climate change, emissions forecasting is a research area that is becoming increasingly significant and has applications in many industries.

The forecasting of emissions from power plants is one potential area for future research. A significant portion of greenhouse gas emissions come from power plants, and precise prediction models can aid plant managers in maximizing their emission reduction plans. The ANFIS model for predicting vehicle emissions can be used as a foundation for creating comparable models for power plants. By including input variables like fuel type, combustion efficiency, and operating circumstances, the model can be modified. Plant managers can lessen their carbon footprint and adhere to emissions regulations by accurately forecasting emissions.

Predicting emissions from industrial processes is another possible use for the ANFIS model. Manufacturing and mining are two industrial processes that contribute significantly to greenhouse gas emissions. These industries can reduce their carbon footprint by optimizing their production processes with the aid of accurate prediction models. By including input variables like production volume, raw material requirements, and energy consumption, the ANFIS model can be modified for industrial applications. Industries can identify areas for reducing emissions and create plans to lessen their carbon footprint by forecasting emissions.

Predicting emissions from buildings is a third possible use for the ANFIS model. Accurate prediction models can assist building managers in maximizing energy efficiency and lowering their carbon footprint because buildings account for a sizeable portion of greenhouse gas emissions. By including input variables like building size, occupancy, and energy consumption, the ANFIS model can be customized for use in building applications. Building managers can pinpoint areas where they can increase energy efficiency and lessen their carbon footprint by forecasting emissions.

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