Utilizing a Neutrosophic Fuzzy Logic System with ANN for Short-Term Estimation of Solar Energy

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Abstract

One of the primary sources of renewable energy in the coming years is thought to be solar energy. Solar energy and other renewable energy sources do, moreover, have a disadvantage in that it is hard to forecast when they will be available. The best use of solar energy is impacted by this issue, particularly when it is combined with other sources. As a result, the organization and economy of solar energy depend on accurate solar energy forecasting techniques. Predicting solar energy shortly is the study's major goal. This paper describes the study of Neutrosophic fuzzy logic with artificial neural networks (NFL-ANN) to anticipate solar photovoltaic (PV) plant output power with the use of specified input factors known as meteorological information, such as sunshine length, humidity levels, temperature, air pressure, and others, artificial neural networks are used to forecast the outcome. NFL represents a generalised logic, which can manage stochasticity learning mistakes and unpredictability that fuzzy logic lacks. It offers the results of the calculation section. Excellent performance computer processors and NFL provide reasonable accuracy estimates of solar plant outputs as well as system reliability to consider environmental factors. The investigation was carried out with the use of MATLAB programming. With the assistance of statistical markers like mean absolute percentage error (MAPE), mean absolute error (MAE), root means square error (RMSE), and determinant coefficient, the suggested NFL-ANN approach is evaluated and compared to other approaches that are already in use. In comparison to existing techniques, the suggested NFL-ANN provides superior accuracy and lesser prediction error, according to the study's findings. This research will be enhanced to forecast power without any loss.

Keywords: Solar energy; short-term; fuzzy logic; neutrosophic logic; prediction; ANN; photovoltaic plant; meteorological; NFL classifier

1 Introduction

The current energy crisis, brought on by a lack of energy to meet daily needs due to population growth, affects the whole planet. The usage of non-renewable energy has peaked in response to the rising requirement for energy.[47] These days, energy evaluation is centered on the necessity for consistent climatic security, sustainable power supplies with minimal carbon emissions, and human wellness.[18] Incorporating renewable energy

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sources into the energy sector is vital in reducing the outflow of ozone-depleting substances and the dependency on imports.[53] Due to the rising environmental concerns caused by the usage of petroleum and coal, which similarly rises daily, renewable energy is currently employed extensively globally.[44] The degradation of non-renewable energy supplies and environmental deterioration result from excessive non-renewable energy usage. The greatest option in this circumstance for meeting energy needs and halting environmental damage is the efficient use of renewable energy sources.[9]

Solar energy is the most abundant and cost-free energy of all renewable sources, and despite its huge usage, it has no negative environmental effects.[61] Figure 1 depicts the benefits of solar energy. Among the most potential alternate energy sources is renewable energy. Because of the increasing demand for power quality (PQ) at an affordable price is crucial to providing sustainable power.[24] As a result, solar energy is among the most efficient resources available since it offers significant potential for generating power.[62] The electricity system needs the help of renewable energy sources like solar photovoltaic (PV) plants, particularly in times of system crisis. Photovoltaic systems are used in solar PV systems to convert solar radiation into electrical energy. As a result, climate patterns significantly impact these sorts of generators. To help grid operators handle the electric balance between power supply and demand, it is essential to anticipate the power output of solar PV plants.[19]

A renewable energy source that turns sunlight that is accessible into electricity is solar photovoltaic (PV) power. Numerous researchers say solar energy is employed extensively worldwide in industrialized and developing nations.[49] By the end of 2017, the total installed solar capacity across all nations was at least 402 Gigawatts. Among all industrialized nations, China has the most solar power installations.[59] Massive solar power installations in affluent nations are also being seen as a response to the issues developing nations face without access to energy, particularly in rural regions. World consumption for manufacturing and electric power is rising due to economic expansion. Solar power plants are highly prevalent in renewable energy.[13] In recent times, solar panel installations have grown yearly. In 2019, 117 gigawatts of solar PV electricity were produced worldwide.[6]

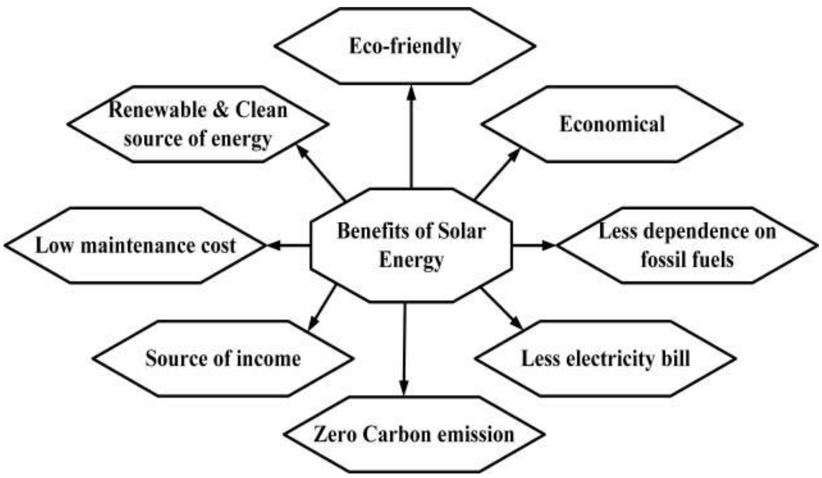

Figure 1: Benefits of Solar energy.

To the degree that economic progression is typically evaluated in a nation's per capita power production, it is a crucial element in a region's fast industrialization and urbanization. Energy consumption is rising, raising the cost of producing and distributing electricity.[42] Moreover, power production relies heavily on polluting fossil fuels that are not renewable. About two-thirds of the world's carbon dioxide emissions come from these fuels, whose current proportion in power generation, if kept constant, will unavoidably cause a sharp increase in the average global temperature and other calamities.[51] Because it relies on the environment and shade, solar energy is unpredictable. The output of solar electricity will become stochastic due to this ambiguity, creating it hard to integrate solar energy into the energy system.[45] Therefore, a solar power plant needs to be properly regulated to be economical. The primary goal of PV forecasting is to anticipate solar radiation or the outcome of solar power plants (SPP). The facility's productivity is forecasted using powerful modeling techniques based on historical information. Therefore, until a solar radiation database is accessible for that specific site, it can't be deployed for newer solar power plants. The dimensions of the solar panels, how they

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are arranged, conversions, and inverters all impact how much energy is produced. When everything is said and done, the outcome will depend on stochastic meteorological circumstances, changing how much radiation will ultimately hit the solar panel.[10] Therefore, accurately forecasting solar radiation on the solar array will deliver information on the long- and short-term generation of solar power plants.

Moreover, several constraints, including high dependability, ideal positioning, appropriate power quality, and cost-effective operations, restrict the use of solar power. Power output variability is a major barrier to the growth of solar-based businesses in their actual production. It restricts solar power's uptake and endangers the grid's security. One of the key elements in estimating photovoltaic (PV) production is solar irradiation. Air pressure and air temperature are two meteorological variables that affect solar irradiation. Predicting ambiguity for solar power is caused by prediction models and measurements of meteorology factor uncertainties. Eliminating these errors is impossible since it is certain that certain instrument-related errors will exist, in addition to observational methodologies. Hence, it is tough to deal with and not straightforward enough to solve the PV power forecast.[11] Solar thermal and photovoltaic systems are the two main types of solar power generation now in use (PV). Solar thermal expertise focuses on sunlight, raising the temperature of heating elements that generate steam. To produce huge amounts of power, steam is employed in steam turbines. As a result, nations, including USA and Spain, have begun using concentrated solar power (CSP) to generate power.[16] However, for CSP to be successful, huge installations are needed. Contrarily, photovoltaics utilizes incoming photons from sunshine to stimulate free electrons in embedding semiconductors, resulting in a build-up of charges and energy generation. Those panels may operate at various scales and are frequently employed on roofs or in open areas, integrating into the architecture of buildings or vehicles or set up in massive grids in solar power plants. PVs have been widely installed over the last few decades, and their consumption has expanded due to their widespread public appeal and structure of reduced tariff costs.[17]

Solar energy has grown dramatically during the previous ten years compared to other renewable alternatives. Precise solar power forecasting models are required to integrate such a huge, uncertain solar generation since erroneous predictions may affect the outcomes in financial penalties and technical difficulties like load generation that can affect frequency stability, voltage regulation, and other factors. A widespread study is also being done on computationally efficient and more reliable short-term solar prediction since the unpredictability of today's weather system significantly reduces the reliability of day-ahead forecasts.[55] In this sense, nations are making great efforts to give harvesting solar energy top attention. But for specialists to successfully construct and develop solar energy systems, access to trustworthy and precise solar radiation data is necessary before investing any effort in any venture.[12] To successfully equip the power network controller to handle changes in solar PV power generation, the present study is focused on creating more precise solar forecasts. Varied grid operative tasks, such as unit commitment, ramping occurrences, and energy futures marketplaces, need various solar predicting timeframes, i.e., intra-day & hour, day ahead.[32]

The main essentially two types of solar plants are grid-connected and standalone. Depending on the kind of solar plant, numerous uses exist for solar power forecast models. When a solar power plant is connected to the grid, precise predictions optimize power distribution. Still, when a system is freestanding, precise predictions are employed to enhance the charge controllers' control techniques.[23] The efficiency of power system planning and management has traditionally depended on accurate energy and load generation forecasting. Many electric power providers anticipate power loads using conventional prediction techniques.[52] While it is challenging to detect nonlinearity when using conventional prediction models because the connection between power demand and parameters influencing power generation is nonlinear. Artificial intelligence and fuzzy approaches have garnered a lot of interest recently to provide increased accuracy, dependability, and convenience in calculating solar irradiance. Three fundamental ideas that make up the structure of fuzzy set theory were similarity measure, fuzzy entropy, and distance measure. The idea of a neutrosophic set that comprises of three parts: indeterminacy membership, truth membership, and falsity membership. The notions of the intuitionistic fuzzy set (IFS), interval-valued IFS, interval-valued fuzzy set, classic set, and fuzzy set have been generalised by the neutrosophic set, a potent universal formal structure.[4] Figure 2 depicts the usage of fuzzy systems and ANN networks. The estimation of the worldwide solar irradiance utilizing different geographical and meteorology characteristics has been done utilizing artificial neural networks (ANN).[7]

Numerous studies are being done on artificial intelligence, or machine learning approaches as an alternative to traditional methods for calculating non-linear parameters. Artificial neural networks (ANNs) are utilized to anticipate the sun's short-term activity depending on various input parameters, including wind, pressure, humidity, and temperature. Different methodologies were used to process the machine learning calculations

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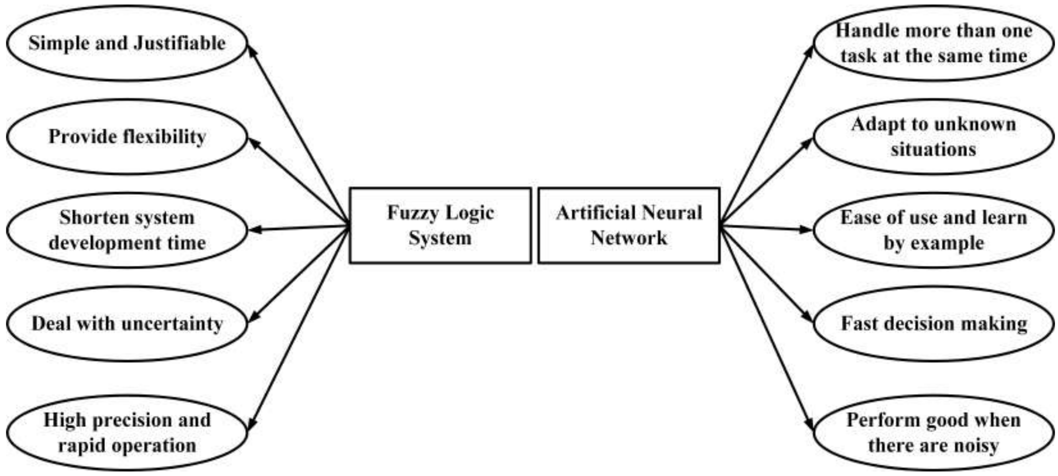

Figure 2: Usage of Fuzzy system and ANN network.

for reliability and estimation. Using a hybrid machine learning approach, fuzzy logic with ANN was employed to forecast the power usage of renewable resources in a short time.

2 Related Work

Because of atmospheric factors, the ramping occurrence of solar irradiance is prone to occur, which makes it challenging to incorporate solar electricity into local power grids. The everyday sun irradiance is influenced by air aerosol, cloud occlusion, temperature, and meteorological conditions. This uncertainty in solar power results in an overloaded or underloaded regional system. Calculating solar radiation and solar power production is crucial for the reliable integration of solar electricity into the local grid. The paper recommends a system to precisely assess solar radiation and solar energy. The global and regional weighting are produced using the feature extractions from the all-sky images. Long short-term memory (LSTM) is employed as the training phase using weights as inputs to predict sun irradiation. The power curve is created by estimating the solar power utilizing anticipated solar irradiation and solar power outputs. The suggested technique is assessed using several performance metrics, such as MAE, RMSE, and the determination coefficient (R2). The test findings demonstrate that the suggested method's effectiveness in estimating solar radiation is exceptional, with reduced MAE and RMSE and greater R2.

Additionally, the effectiveness of the solar power estimation using the suggested technique is extremely similar to the effectiveness of the real prediction. Due to its inability to retain data for a prolonged time, this strategy is ineffective. Occasionally, to forecast the present outcome, a reference to specific data that was saved a long time ago is needed.[15]

The installed capacity of photovoltaic panels makes up a growing share of the power grid, and the variability of solar irradiance significantly impacts its sustainability. For the safety of the power system and the smooth operation of energy market activities, reliable solar radiation forecasting is a crucial necessity. Deep learning is now the most popular approach for predicting solar radiation, and its choice of information and structure determines the network's speed and accuracy in making predictions. This work proposes a unique LSTM system based on the attention mechanism and genetic algorithm (AGA-LSTM). The attentiveness strategy assigns each component a different weight, so the modelling may focus on the key aspects. The direct normal irradiation and global horizontal irradiation are predicted after 5, 10, and 15 minutes using the time series processing and memory capability of the LSTM. At the same time, the model's design and information-selecting variables are adjusted by genetic algorithms. Two years of information from the National Renewable Energy Laboratory's Solar Radiation Research Laboratory website was utilized to develop and estimate the suggested AGA-LSTM framework. The test results demonstrate that the AGA-LSTM model's predictive accuracy under the three-prediction scaling is below 20%, significantly increasing predicting accuracy compared to the linear

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system and certain widely used approaches. This approach is ineffective since it might be costly to compute and challenging to debug.[22]

There is a strong need for energy in several locations, including residences, clinics, businesses, transportation, and communication. Since it can be created and reused again, renewable energy is a novel sort of energy that is being utilized more and more to meet the need for power. It is challenging for several research activities to assess the pace of renewable energy since it is a natural material that is an intermediary and unpredictable. This work employs a mixed machine learning approach to resolve this issue by accurately forecasting the energy content of natural resources. To enhance the efficiency and prediction of the use of renewable energy, hybridization machine learning combines Support Vector Regression (SVR), CatBoost algorithms, and Multilayer Perceptron (MLP). Findings from the training and testing phases of the developed framework dataset are assessed, and the outcomes are then contrasted with those from other recent methods. The ultimate findings demonstrate that the suggested hybrid machine learning approach outperforms others regarding predictive level, cost rate, and overall system efficiency. This approach is inefficient since it will execute inadequately when the amount of features for every data point is greater than the amount of learning data samples.[1]

The discovery of basic innovative aspects, applicability demonstrations, and industrialization advancement for the full chain designing, integration deployments, and sub-module promotion are only a few sectors where systematic study is required to build rural energy sources. This research firstly examines the short-term impact of decision tree algorithms on the revival of power building in rural areas. Next, using various ID3 decision tree techniques. It integrates the benefits of the two methods, conducts attributes complementing screens, and determines a suitable threshold for the Relief features selection procedure. Finally, this study uses the Relief method for selecting features and the ID3 decision tree technique to construct a feature selection model. The decision tree method gets and screens the initial result. To achieve the testing of inconsequential characteristics, the threshold of the Relief feature selection method is fixed during the procedure, and the characteristics acquired by the Relief feature selection algorithm and the characteristics acquired by the ID3 decision tree technique are evaluated and accompanied. It has a specific promotional and reference value by developing the use method of optimum rural solar energy space planning. Due to the risk of overfitting the training set, this strategy is ineffective.[8]

The transition from fossil fuels to sustainable energy sources will be one of the major worldwide developments in the coming decades. Accurate estimates of the usage of renewable power appear to be important on both a national and global level. Grey prediction systems with a single variable are among the top options for such forecasts when few previous data points are available. But when a system's dynamics depend on just one parameter, this appears somewhat speculative. This study proposes a unique method that incorporates the effects of exogenous factors through modifications of the multivariable grey forecasting model.

Additionally, states and variables in the suggested technique are progressively calculated using the conventional Kalman filtering rather than the least squares approach. The Kalman filter stage also includes the genetic algorithm to account for unidentified noise statistics. Utilizing information from 1990 to 2015, it is used to calculate and anticipate Thailand's consumption of renewable energy and its related components, validating the suggested strategy's effectiveness. The findings demonstrate that the hybrid technique offers higher parameterization and predicting performance when compared to the multivariate grey model utilizing the least square technique. As a result of its inability to provide an ideal estimate, this strategy is ineffective.[8]

Solar energy is a significant renewable energy source and plays a significant role in replacing fossil energy producers and reducing carbon emissions. Moreover, the economic cooperation of solar production into the current power systems is severely hampered by the intermittent output power brought on by the unpredictable solar radiation, necessitating efficient forecasting techniques to increase solar predictive performance. This study proposes and uses a unique, enhanced radial basis function neural network (RBFNN) approach to anticipate short-term solar energy generation. The linear and non-linear variables of the radial basis function neural network structure are trained using a recently devised meta-heuristic method called competing swarm optimization. The suggested model was tested using nonlinear benchmark functions before being used to predict the solar power output of a real-world scenario in the Netherlands. As shown by the numerical solution, a valuable tool for solar power prediction is the suggested competing swarm optimized RBFNN framework, which might achieve superior reliability compared to its competitors. This approach is inefficient because each hidden layer node must calculate the radial basis function for the input data vector during categorization, which makes it slower than multilayer perceptron's even if radial basis function networks are quicker for learning.[31]

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A crucial element of the economically viable implementation of great exposure stages of photovoltaic (PV) schemes is now solar predictions. To describe a high-resolution probability behavior of solar, this research introduces two brand-new stochastic predictive models for solar PV. Initially, PV power and solar irradiance are predicted using an uncertain basis functional technique. The Gaussian, Laplace, and uniform distributions are three potential distributions for uncertain basis functions. In the second place, stochastic state-space models describe how solar radiation and PV power production behave. The state variables and system parameters are repeatedly calculated using a filter-based expectation maximization and Kalman filtering approach. This allows the system to accurately predict solar signal variations, both minor and big. The predicting techniques that have been presented work well with real-time tertiary dispatch controllers and optimum power control systems. The solar irradiance and PV power observations from a 13.5 kW PV panel on the facility's roof are used to evaluate the PV forecasting algorithms. The outcomes demonstrate a significant enhancement in the predicting reliability of the entire energy generated compared to traditional time series estimating systems. The lengthy processing time makes this strategy ineffective.[60]

A critical challenge for the administration and planning of renewable solar energy production systems is the precise solar irradiation prediction. To correctly anticipate solar radiation, the current research seeks to provide a novel machine-learning prediction model based on improved ANNs. The development of the predicting history and ANN structure is proposed as an evolutionary framework to achieve this goal, generating several models for various timeframe horizons up to 6 hours in advance. The tests utilize a dataset of 28 Moroccan cities to examine how well the suggested systems function under various climatic situations. The suggested framework is then assessed using a zoning scenario that enables the algorithms to reliably predict solar radiation in locations without such information. To evaluate and contrast the obtained results, two more cases are employed. With NRMSE ranging from 7.59% to 12.49% and NMAE ranging from 4.41% to 8.12% as the highest performances for solar radiation estimating from 1 to 6 h ahead, accordingly, the obtained findings for all analyzed situations indicate strong generalization skills. The effectiveness of the suggested HAEANN systems is then compared to three alternative methods, demonstrating their superiority. Due to the high data requirements for training, this approach is ineffective.[41]

Over the past ten years, the development of renewable energy, particularly wind energy, has exceeded all expectations. The dependability of the power system can be improved by using short-term probability wind power forecasts. However, owing to uncertain factors like wind velocity, short-term predicting of electricity produced by wind turbines has a significant error rate; thus, it is crucial to develop a solution to improve predictive performance. As a result, a unique forecasting approach with excellent reliability in comparison to existing techniques is provided in this study. This study uses a novel Improving Kernel Density Estimation (IKDE) approach to evaluate the potential for wind energy to gain from the excellence of different forecasting techniques. By offering varying compactness efficiency, the mixture of various estimation techniques and the proposed technique may create the functionality of probability predictions. A strong technique for analyzing backgrounds and foreground characteristics is the KDE approach. A detecting approach based on an IKDE system is designed to improve the effectiveness of the KDE method. The fundamentals of the IKDE approach are the suitable bandwidths, comparison thresholds, comparing backgrounds sample learning arrays, and an improved sampling updated mechanism for sample learning arrays. The variables of the IKDE framework are streamlined using two layers of optimization.

Consequently, this approach and four other ways have been put into practice on 10 wind farms to demonstrate the effectiveness of the proposed method over other techniques. The simulation findings reveal that the suggested technique's accuracy rate is approximately 3.8% better than previous approaches due to its enhanced design. Because this strategy is constantly biased, especially close to the limits, it is ineffective.[26]

With the rising use of renewable energy in the power system grid, one of the most crucial subjects to be addressed is the smart grid, which aims to increase grid energy efficiency by controlling the link between consumption and production. Both the output power production from various renewable energy sources, as well as load predictions, are essential components of this procedure. Predicting the model's accuracy is crucial when producing and using new energy. The demands of the new renewable energy production and its uncertainty cannot be handled by the conventional methodologies utilized in the literary work completed for load prediction. To enhance the overall system effectiveness and quality, this research suggests a unique method for short-term load prediction depending on a hybrid of several approaches and employing cluster analysis. Various Wavelet, Kalman filtering (KF), and ANN techniques are utilized in these studies. Based on the clustering algorithms, six distinct models are suggested. Experiments showed that the suggested models performed better. The information utilized in this article is scaled because it is commercialized information. The suggested work is verified by utilizing various datasets for two sites in Egypt and Canada. This approach requires much computational power, making it ineffective.[21]

3 Methodology

Machine learning is among the gaming technologies that have changed the most over the past year. Machine learning allows businesses to quickly achieve the desired output in the increasingly expanding cooperative environment. A hybrid machine-learning approach is created by combining two distinct machine-learning techniques. One of the foundational techniques for machine learning is supervised learning. For this strategy to work, a precise labelling data set is required. The technique and the connection between the trained and new data sets are both enhanced by using this method. The benefit of unsupervised learning is that it may be used with unlabelled data. With this, post-deployment enhancement was offered in place of a supervised learning method. Human existence is inspired by reinforcement. This application is designed to offer potential answers to the provided data. The listed and unlabelled conditions apply to this work; the training and evaluation data may be distinguished after being collected and analyzed using renewable energy. The final result is tested for errors after the information has been run through a hybrid machine learning algorithm, and the result has a high precision and a low error rate. Figure 3 depicts the overall process flow diagram for the proposed NFL-ANN approach.

3.1 Data collection

Solar energy information for a period of one year from April 2020 to March 2021 is taken into account in this study and was achieved from the Solar Energy Centre (SEC), which has since existed into the National Institute of Solar Energy (NISE), Gurugram, and the Indian Meteorological Department (IMD), India. The input variables for forecasting solar energy include meteorological variables such as sunlight hours, air temperature, wind direction, humidity levels, and dew point. The outcome variable is worldwide solar energy. The reliability of the model has increased significantly with the addition of these factors. This information is gathered over 24 hours using Indian Standard Time. When there are available sunlight hours according to Local Appearance Time, Campbell- Stokes is used to quantifying them. Hygrometers are used to detect relative humidity; bimetallic thermographs are used to monitor air temperature and dew point. Electrical anemographs determine wind speed, and pyranometers monitor global sun energy.

3.2 Data normalization

To avoid converging issues, standardize data such as ambient temperature, dewpoint, global solar energy, sunshine hours, humidity levels, and wind velocity and describe them using a 0.1-0.9 range as stated in Equation 1.

$$\mathrm{Sd} = \left(\frac{\mathrm{Z_{mx}}-\mathrm{Z_{mn}}}{\mathrm{S_{mx}}-\mathrm{S_{mn}}}\right) \times (\mathrm{S}-\mathrm{S_{mn}}) + \mathrm{Z_{mn}} \tag{1}$$

Whereas Sd stands for the standard data set, Z_{mx} for maximum limit, Z_{mn} for minimum limit, S_{mx} for maximum data range, S_{mn} for minimum data range, and S for the measured data set.

3.3 ANN- Artificial neural network

It is a replication of biological neural systems that efficiently links different parameters to a greater amount of ambiguous data points. ANN models don't need complicated mathematical bases or equations to link different criteria. As a result, ANN takes less computing work when coupling any quantity of parameters with

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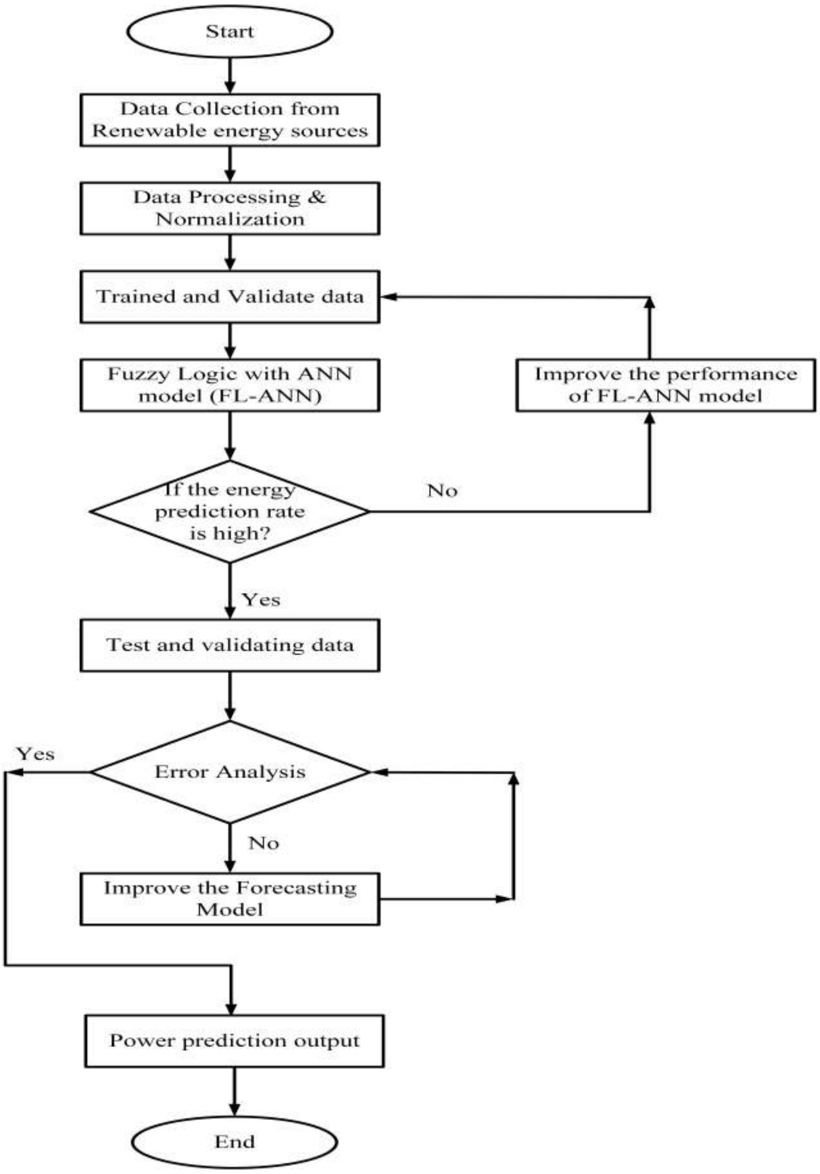

Figure 3: Overall process flow diagram for the proposed approach.

many ambiguous data points than previous approaches. Learning an ANN using importing data is known as supervised learning or training. Similar to the neurons in the human brain, ANN is made up of many neurons. A fractional quantity denoted weight connects these neurons. To forecast correct outcomes throughout the learning phase, the weighting is modified. Whenever the inaccuracy achieves a tolerable level, the weight values become consistent. Its levels of the organization are input (which accepts information), hidden (which processes data among source and destination nodes), and outputs (which sends computed data). Figure 4 depicts the ANN structure.

Typically, the quantity of neurons in the hidden layer is determined using Equation 2, which depends on the quantity of learning data points and input and output neurons. The number of hidden layers is frequently determined through experimentation. The whole collection of data for an input-output parameter is split into two groups: the learning data set, which contains a larger proportion of the data points and is utilized for training the neural network, and the validating data set, which contains the balance data points. Neural networks incorporate parameters of input-output together with their learning data points. The training of this network continues till the acceptable error is reached. That once allowable error is determined, the learning algorithm is verified by integrating the scores of the testing data point input variables and forecasting the measured value of the model outputs. If the difference between the predicted and observed outcome is within the allowable

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limit, the qualified neural network may be the best for forecasting. These anticipated values for the verifying data set's output variable are compared to the corresponding actual values for the outcome variable.

Different training algorithms are utilized for training neural networks, including the training process, learning variation, number of hidden neurons, and transfer function. There are several training functions, learned variation, and transfer function options. An appropriate amount of epochs are used for learning. The neural network forecasts the variable output values for the associated input parameters for the appropriate training procedure and learning epochs. Suppose the inaccurate score is less than the permitted value. In that case, the generated neural network with that set of learning algorithms may be chosen as the most effective neural network with the best learning approach. When the error is bigger, the neural network is trained using the same training method for various epochs or a new training approach until the error is within acceptable limits. The best neural network's predictions of outcomes utilizing validating data points verify the generalizability of the trained network.

$$N_{nh} = \left(\frac{I_n + N_O}{2 + \sqrt{D_{tn}}} \right) \tag{2}$$

N_{nh} is the hidden neurons, I_n is the number of inputs, N_o is the neuron's output, and D_{tn} is the number of learning datapoint. Every neural network has a threshold level, and the final result is only forecasted whenever the summation of the input data is multiplied by the weighting factor above the threshold level, as shown by Equation (2).

$$Z_o = \sum_{k=1}^{n} W_{ok} \times y_k \tag{3}$$

Z_o is the outcome of the neural network, W_{ok} is the weighting at the k^{th} neuron, and y_k is the k^{th} neuron's values based on various morphologies and traits. As shown in Figure 4, interconnections among layers have a weight factor, and every layer comprises neurons that analyze the input variables and create an output.

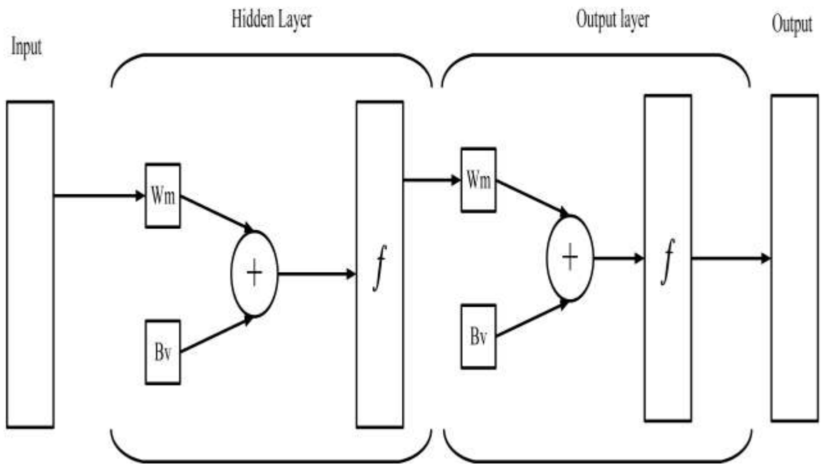

Figure 4: Overview of the ANN approach.

Based on the chosen design, adjustable synaptic weights connect all or a part of the neurons in a layer with those in the layer above and below. The number of hidden layers and overall neurons in every layer is based on the particular models, the converging rate, the scope for generalization, the underlying physical mechanism, and the training data the system will replicate. Equation 4 specifies the connection between every layer and the one before it or after it.

$$V_{oh} = f\left(W_m + B_v\right) \tag{4}$$

W_m is the weight matrix, B_v is the bias vector, V_{oh} is the hidden layer's output vector, and f is the layer's transfer function.

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3.4 Neutrosophic-based Fuzzy logic system

Neutosophic logic, which has been predicated on Abraham Robinson's unconventional analysis from the 1960s, has been recently put out by Florentine Smarandache. To describe the algebraic concept of incompleteness, vagueness, imprecision, uncertainty, inconsistency, ambiguity, contradiction, and redundancy, neutrosophic logic has been created. Every statement in neutrosophic logic was predicted to possess a percentage of reality in subset U, a rate of unpredictability in subset J, and a rate of falsehood in subset G, wherein T, J, and G are conventional or unconventional actual subsets of $]^{-}0,\ 1^{+}[$:

$$with\ supU\ =\ u_{sup},\ infU = u\_inf$$

$$supJ = j_{sup},\ infJ = j\_inf$$

$$supG = g_{sup},\ infG = g\_inf$$

and $o\_\mathrm{sup} = u\_\mathrm{sup} +\ j\_\mathrm{sup} + g\_sup$

$$o\_\mathrm{inf} = u\_\mathrm{inf} +\ j\_\mathrm{inf} + g\_inf$$

The sets T, J, and G might be any actual sub-unitary groups, such as infinite, or finite, continuous or constant, single-element, a combination or intersections of different subsets, etc. They are not have to be intervals. They could also cross paths. T, J, and G have been subsets statistically. This research employ a portion of reality, rather than a single number, since this research frequently cannot find the precise rates of falsity and truth but must make approximations. For instance, a proposition may be from 30 to 40% true and from 60 to 70% false, or, in the worst-case scenario, from 30 to 40% or 45 to 50% accurate (as per to different analyzers), and 60% or anywhere from 66 to 80% false. As it represents a more accurate and justified estimate, neutrosophic likelihood (by employing subsets rather than numbers as elements) must be employed for better participation, according to neutrosophic logic[54]

Fuzzy logic can anticipate relevant responses for all data sets within the ranges of different indicators since it works with ranges rather than specific data points. Fuzzy logic's effectiveness is based on human expertise. Mamdani and Sugeno are the two modules that make up fuzzy logic. The response variables contain data points in the Sugeno modules of fuzzy systems. The input variables have different ranges, unlike the Mamdani modules of fuzzy systems, where input and output variables are separated into ranges. Fuzzy logic is divided into two divisions, the first presents the influencing (input) variables, and the second displays the effectiveness (outcome) variables. Every input/output parameter's whole span is split into several smaller spans. Every tiny range's variability is expressed by an appropriate primitive form, such as a triangle, trapezoid, sinusoidal, or Gaussian. This basic form is chosen considering the fluctuation pattern in the information in any range. Every range with an appropriate primitive form is called a membership value. The behavior of imported input-output data determines the number of membership functions and the boundary span of every membership value. Regulations are constructed in the fuzzy modular's rule builder depending on the values of the input-output parameters once membership functions have been chosen. The data is divided into training and validation sets to ensure the correctness of the fuzzy system that has been developed.

Regulations use "IF-Then" statements and "AND," "OR," or "NOR" Booleans to link the input and output variables. As a result, rules serve as the connection between input and its corresponding matching outputs. Because there are fewer rules due to the reduced quantity of data points, it could anticipate erroneous results for certain imported input data. A massive proportion of data points results in more regulations, which improve effectiveness, but occasionally overfitting (where there might be several outcome values for a single imported input data) also produces erroneous results. In the fuzzy modular's rule analyzer, regulations are put into action. The regulation analyzer is separated into two divisions. The first encompasses all input variables and their fuzzy membership, and the second contains the output values and their fuzzy membership. Results obtained are anticipated depending on the selected criteria by importing input data from the training set. Suppose the anticipated resulting value and the actual and estimated values for every input value are closer to the training set. In that case, the specified regulations are the best rules for the created fuzzy system. If not, regulations are altered in the norm builder to get more precise outcomes. By importing their input data, a fuzzy inference system with the best rules is utilized to forecast the outcomes of the validation data.

When applied to the validating data set, a fuzzy inference system can be expanded to cover all potential input variable ranges if it produces reliable outcomes. Certain defuzzification techniques are utilized to forecast the

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precise rate from the range of output parameters depending on the importing input data and the criteria. There are several defuzzification methods, including the mean of the maximal, centre of gravity, last of maximal, centroid, middle of highest, the bisector of the region, and centre of the area, among others. Additionally, the user can create its defuzzification methods and fuzzy membership. The load forecasting technique, dependent on fuzzy logic, was created using a MATLAB program. As seen in Figure 5, the system is a five-input, one-output Mamdani model that accordingly depicts solar irradiation, ambient temperature, rainfall data, relative humidity, time, and output power. Owing to its interpretability and simple character, the Mamdani approach is preferred over the Sugeno technique for usage in decision-making support systems. Additionally, it enables a more humane interpretation of the knowledge. Since people seldom tend to draw conclusions or pass judgement in clear-cut situations, all the components mentioned by neutrosophic-based fuzzy logic have been crucial to human thought. Inaccuracy in human systems may result from the inadequacy of the understanding that humans gain through their observations of the outside world[37]

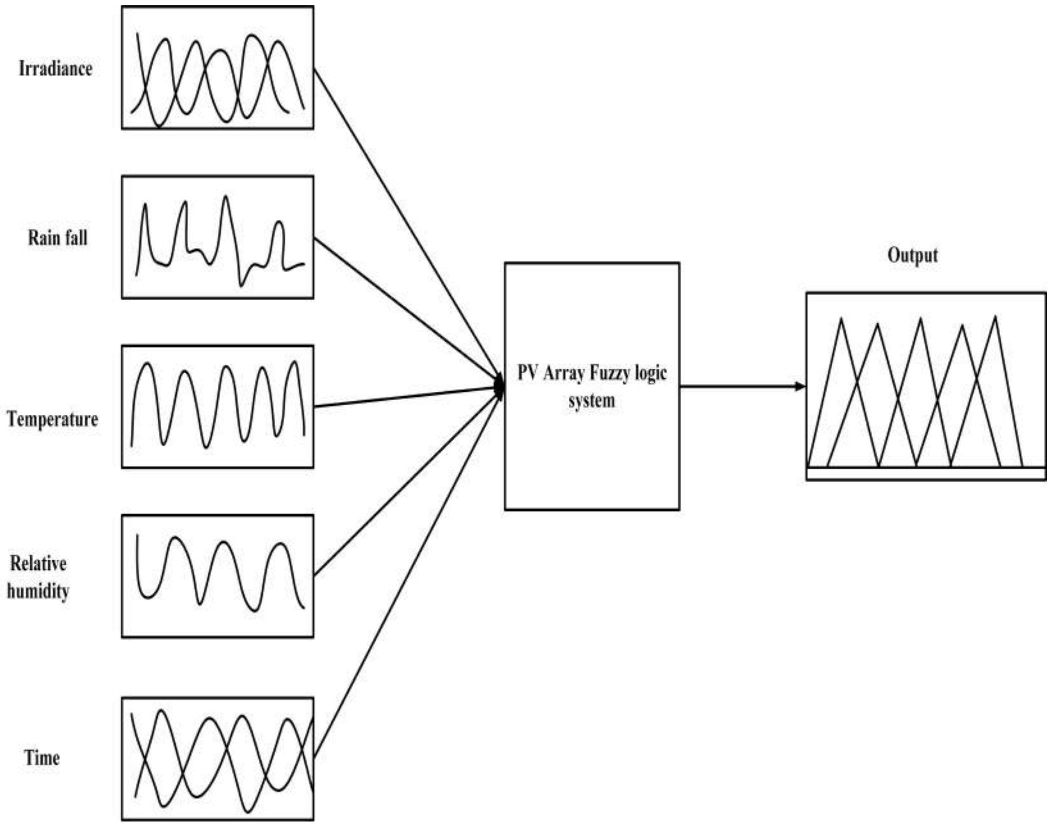

Figure 5: Overview of Fuzzy logic system.

3.5 ANN with Neutrosophic-Fuzzy Logic (NFL) Model

The fuzzy and neural network approaches were used in this study to provide a novel technique for forecasting solar radiation. Sky conditions, temperature, and time data all substantially impact solar irradiance. NFL describes the connection between the real scenario and the categorized circumstances after training neural networks in various settings. The historical data will be utilized to train neural network models for each hour of the day. Three sky conditions—sunny, rainy, and cloudy—are categorized every hour. Solar irradiation still has considerable variation, even under identical meteorological conditions. Below each type of sky, the differences may be determined by the temperature. Three typical average hourly temperature values were chosen for every weather condition and hour. These categorize every weather condition as mild, medium, or powerful. The number of data points used for neural network training, validation, and evaluation. These are utilized for learning in around 70% of cases. To verify that the networks can generalize and halt training before overfitting, approximately 30% of the datasets are utilized. Figure 6 neural network comprises 8 input units, 25 hidden units, and one output in the output units. Every neuron in the neural network has a tangential sigmoid as its activating function.

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Moreover, the meteorological data are crucial input of the ANN-based solar prediction system. The generated solar radiation would fluctuate significantly, and prediction inaccuracy would logically rise in the event of abrupt variations in solar radiation or warmth on the forecasted day. In conventional estimation techniques, the ANN learns the trend of similarities by using data from all comparable days. Moreover, memorizing the data for all comparable days is rather difficult. It is useless if the weather abruptly changes on a certain day or if there is no information on the characteristics of similar days. To analyze meteorological data arriving from the meteorological sensors, a system must be included in the ANN. The research suggests using fuzzy filtration for various inputs in the existing meteorological data. To categorize the cloudiness indices as additional input to the neural network, a fuzzy pre-processing framework is added to the neural network to identify data association among rainfall, temperature, radiation humidity levels, and the time of day (I8). Whereas the membership functions for rainfall are binaries "1" and "0," those for humidity levels are light, medium, and excessive. The statistics examination of the likelihood function of humidity levels and rainfall yields the membership function parameters.

The suggested solution will produce more accurate prediction outcomes and do away with the requirement for highly expensive sky imaging systems that supply cloud-covering data. The calculation of the error between the results of the neural network (mth timeframe) and the perfect weather models is also provided to reduce error for the future 5-min forecast (m+1th timeframe) (mth timeframe). The error then spreads from the output nodes back to the input nodes of the neural network. The modified ANN model's inputs for the error-checking parameter (I7) are provided by

$$I_{7,\ m+1} = \left(\frac{Z_m}{I_{6,\ m}} \right) \tag{5}$$

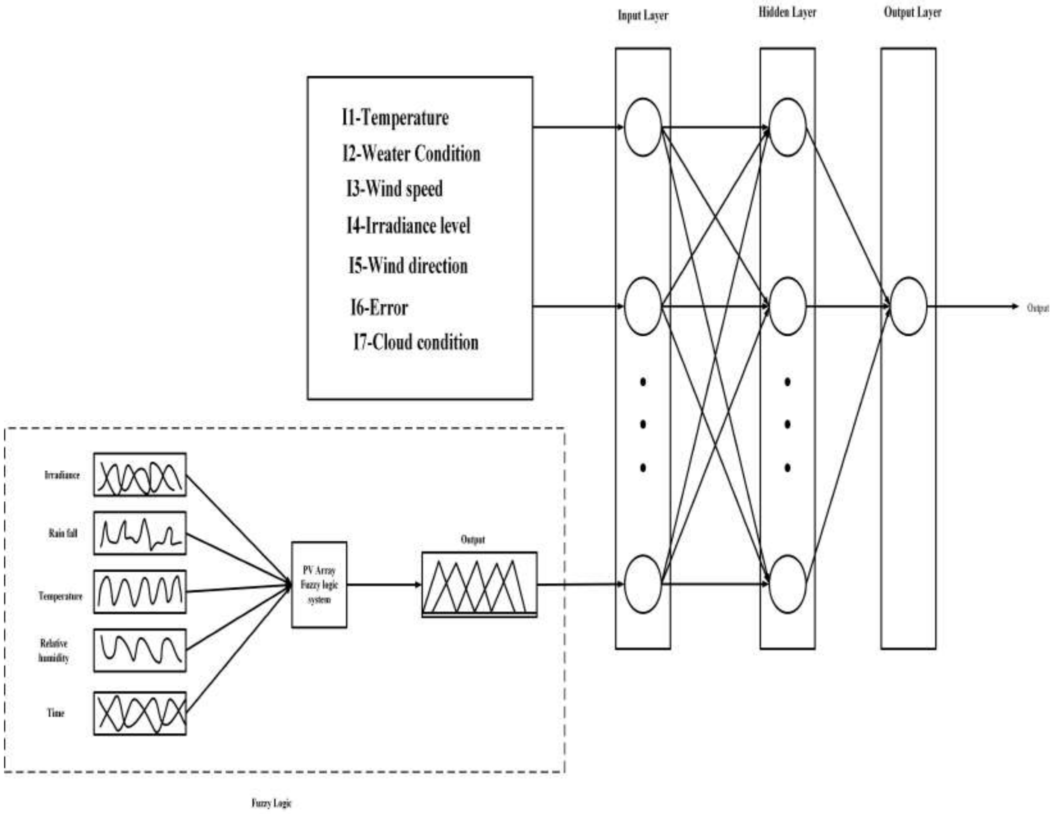

Figure 6: Structure of proposed NFL-ANN approach.

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4 Results

The weather station used to collect the data input is in India. The NFL-ANN algorithm is trained using meteorological data from the previous year (April 2020 to March 2021) to estimate irradiation. MATLAB is used to implement the better ANN presented and the NFL pre-processing. A solar PV array's characteristics have been studied. Using NFL and ANN, forecasting methods have been built using information from solar PV arrays. To evaluate the outcomes of the NFL-ANN models, it is necessary to compare the expected capacity values with the real testing results. The efficacy of the agency is assessed using these three different metrics. The determinant coefficient, mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE), which may be calculated from both the real and the estimated information, are two often used markers of forecasting accuracy. This research aims to demonstrate that adding NFL with ANN pre-possessing would enhance forecast error and short-term power prediction compared to other traditional models. From the study's outcome, the suggested NFL-ANN may quickly increase solar power forecast accuracy.

RMSE: The root means square of all the errors is known as the RMSE. Although RMSE is a useful metric for gauging accuracy, it cannot be used to compare forecasting accuracy with actual data.

$$RMSE = \sqrt{\frac{1}{M}\sum_{l=1}^{n}\left(Z_l - \hat{Z}_l\right)^2} \tag{6}$$

MAPE: It is a measurement of how statistically accurate a forecasting approach

$$MAE = \frac{1}{M}\sum_{l=1}^{n}\left|Z_l - \hat{Z}_l\right| \tag{7}$$

$$MAPE = \frac{1}{M}\sum_{l=1}^{n}\left|\frac{Z_l - \hat{Z}_l}{Z_l}\right| \times 100\% \tag{8}$$

R2 Square. This analytical indicator shows how much ambiguity an independent variable can describe.

$$R^2 = 1 - \frac{\sum_{l=1}^{n}\left(Z_l - \hat{Z}_l\right)^2}{\sum_{l=1}^{n}\left(Z_l - \bar{Z}\right)^2} \tag{9}$$

The efficiency of the proposed NFL-ANN compared with LSTM, ID3 Decision Tree, Support Vector regression, Swarm-optimized radial basis function, AGA-LSTM, Analog Ensemble Method, and CNN will be denoted in table 1. Its performance analysis is represented in Figure 7.

Table 1: Performance comparison in terms of error metrics.

Technique	**MAE**	**MAPE**	**RMSE**	**R2**
LSTM	0.67	0.76	0.76	0.62
ID3 Decision Tree	0.57	0.48	0.58	0.55
Support Vector regression	0.44	0.49	0.62	0.92
Swarm-optimized radial basis function	0.88	0.65	0.78	0.55
AGA-LSTM	0.52	0.88	0.63	0.65
Analog Ensemble Method	0.72	0.70	0.52	0.77
CNN	0.35	0.44	0.44	0.89
Proposed NFL-ANN	0.24	0.30	0.28	0.98

Table 2 accurately estimates the proposed system during sunny, rainy, and cloudy conditions. The performance analysis of accuracy is represented in figure 8. The proposed NFL-ANN system accuracy is calculated by using the below equation:

$$A_c = \left(\frac{tp + tn}{fp + fn + tn + tp}\right) \tag{10}$$

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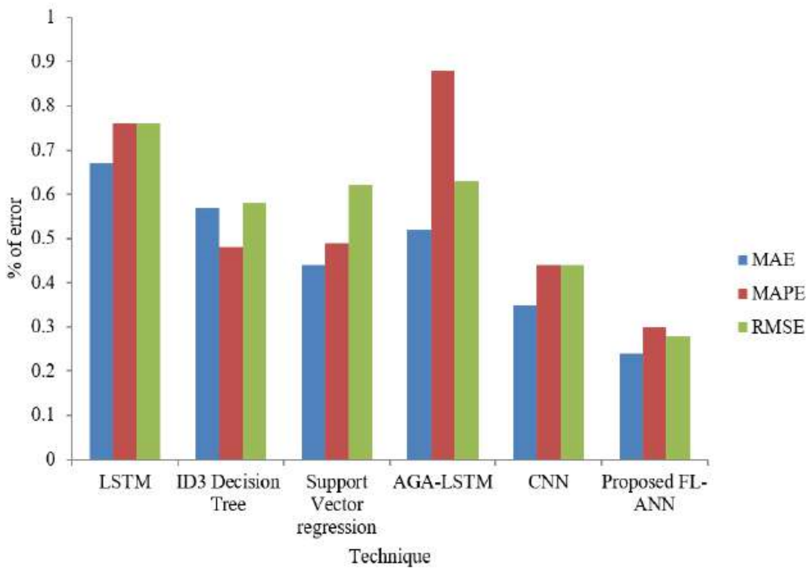

Figure 7: Analysing error performance of the proposed NFL-ANN approach.

Table 2: Accuracy calculation based on three weather conditions.

Technique	**Accuracy (%)**		
	Sunny	**Rainy**	**Cloudy**
LSTM	0.95	0.88	0.92
ID3 Decision Tree	0.94	0.79	0.85
Support Vector regression	0.96	0.94	0.95
CNN	0.98	0.95	0.96
Proposed NFL-ANN	0.99	0.98	0.99

The time needed to complete a computing operation is called computational time. The estimation time for solar energy prediction is represented in table 3, and its performance assessment is represented in figure 9.

Table 3: Accuracy calculation based on three weather conditions.

Technique	**Computation time (second)**
LSTM	0.42
ID3 Decision Tree	0.38
Support Vector regression	0.66
Swarm-optimized radial basis function	0.55
AGA-LSTM	0.42
Analog Ensemble Method	0.45
CNN	0.35
Proposed NFL-ANN	0.22

5 Discussion

Accurate simulations of the production of dependable, economical, renewable power sources and eco-friendly energy from domestic will benefit the whole society and leave behind a wholesome environment for subsequent generations. Fuzzy logic aids in translating the system's fuzziness into an accurate, measurable metric.[33] As a result, modelling based on NFL may be utilized for effective energy management to find workable solutions.

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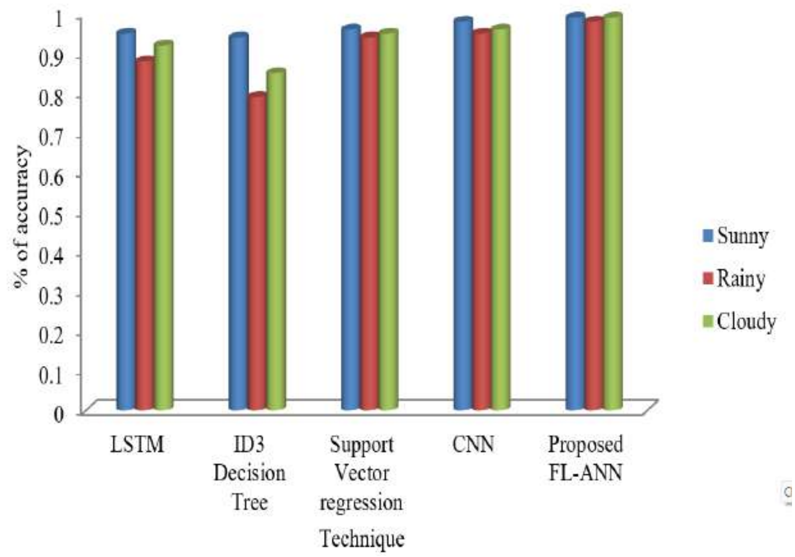

Figure 8: Analysing accuracy of the proposed NFL-ANN approach.

Fuzzy logic is a type of several-valued logic that interacts with actuality. It focuses on approximate reasoning incorporating linguistic values instead of clear ones. The idea of truthfulness, which may be either entirely true or false, is handled by fuzzy systems (0–1). Numerous fields have used fuzzy logic. A probabilistic and fuzzy system is two alternative approaches to convey ambiguity. Although likelihood theory employs the idea of subjective likelihood, the fuzzy framework uses the idea of fuzzy set membership. To minimize the primary energy inputs and pollution emissions, fuzzy c-means clustering and fuzzy set theory were used to condense the information used in power management.[25] Using fuzzy-random intervals optimization, Cai et al. have determined the best plans for energy management systems under various ambiguities.[57] The approach included fuzzy stochastic computing, mixed integer, and periodic linear programming. NFL has been used to efficiently capture and condense the information and ambiguities included in energy modelling.[50]

Ludwig developed a revolutionary fuzzy-based methodology to evaluate the diverse energy conversion methods while considering environmental factors. It concluded that renewable energy must be employed for sustainability.[38] A fuzzy-based expert system was established by Kaminaris et al. to identify a distinct fuzzy action priority rating for a renewable energy system. The factors take the life cycle assessment into account. Thus, this prioritization ranking will be very helpful to operators when deciding on an electrical system that uses renewable energy sources.[29] The development and execution of a fuzzy cognitive maps-based decision analysis toolbox for the design of renewable energy sources have been described by Kyriakarakos et al., and it has been evaluated on the island of Crete.[35] This toolset will be extremely helpful for a judgment to seek to analyze their expenditures on renewable power sources in local areas. It has been discovered that fuzzy logic is also widely employed as a technique for assessment and evaluation.[36]

Constructions now utilize fuzzy intelligent systems and fuzzy-based hierarchy analysis to boost comfortable while consuming less energy, leading to passive construction methods.[40] To attain the best visual and thermal comfort levels inside the living and functioning area, Use a fuzzy logic intelligent system to develop solar houses.[20] Jaber et al. used multiple criteria evaluation to contrast space heating systems depending on traditional and renewable energy sources utilizing the value-to-price ratio from fuzzy AHP.[28] It was discovered that heating systems powered by renewable energy (specifically solar and wind) were preferable. Yu and Dexter deployed hierarchy fuzzy supervisor controllers to optimize the functioning of a lower-power building that employs solar energy for internal heat and cooling.[56]

The comparative relevance ratings of diverse renewable energy diffusion projects in Korea are determined utilizing fuzzy AHP employing fuzziness in the range values based on five factors: technology, business, economic, ecological, and policy-related.[27] The greatest renewable power source for Indonesia's generating electricity was chosen using fuzzy AHP.[58] To evaluate the relative scores showing the significance of power safety considerations in China, Ren, and Sovacool employed fuzzy AHP.[48] In fuzzy modelling techniques,

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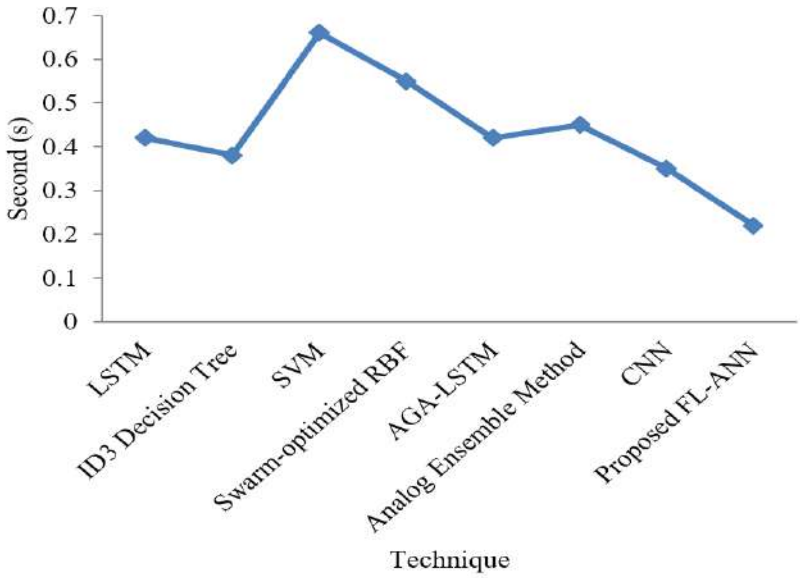

Figure 9: Analysing accuracy of the proposed NFL-ANN approach.

such ranging values provide crisp quantified ratings. Artificial neural networks can resolve several significant and complicated issues due to their capacity to understand vast samples.[14] The feed-forward component is the most prevalent neural structure in the system. Standard neural networks are constructed from several computing units called neurons. The biases and weights of the hidden and output layers are constantly optimized until the outputs neuron scores can filter out erroneous inferences.[43] Regression issues were effectively addressed using this strategy.[2] ANN techniques may handle nonlinear systems. The constraints still include issues with overfitting, local features, randomized beginning data, stringent trained information required, and increasing complexity brought on by multi-layered designs.[3]

Karatepe et al. discuss PV module simulation utilizing ANNs. The training set and other empirical correlations were examined using a variety of selected attributes.[30] The acquired comparative findings for the suggested models were good and may be applied to any investigations involving power electronics and PV modules that can be conducted online. Kusama et al. employed data mining backed by numerical simulations to improve solar cell performance. The outcomes point to a fresh approach for creating better electrolytic solutions by utilizing base additions for dye-sensitized.[34]

For a solar water heater (SWH), For developing a failure diagnosing system (FDS) that comprises an estimation module, a residue estimator, and the diagnostic module. The system may predict both pipe insulating and collector problems.[39] The system is validated using the different input values for fault conditions. Sunlight duration, highest temperature, humidity levels, latitudinal, longitude, the day of the year, everyday global irradiance, heat, overall clouds, altitude, clearness index, mean wind speed, mean temperature, months, mean cloudiness, reference clearness index, atmospheric conditions, mean diffuse radiation, and mean beam was the geographic and meteorological variables used as input parameters to ANN models for solar irradiance forecasting.[5] With the effect of regional climatic factors, training techniques, and ANN architectural setup, the established predicting criteria for ANN systems vary. The study can, therefore, confidently state that selecting the appropriate input variables is crucial to reliably and more accurately anticipate solar irradiance.[46]

6 Conclusion

Power generation depends heavily on renewable resources. It is essential to estimate or anticipate the energy in a particular region. An enhanced solar forecasting technique based on Neutrosophic fuzzy logic with artificial neural networks has been described in this research (NFL-ANN). To reduce prediction error and boost prediction accuracy, the suggested model also features an enhanced error-correcting parameter. The created model is trained using the meteorological information collected from an Indian weather station. The empirical results demonstrate that the error-correcting factor's capacity to adjust its error checking may significantly increase solar radiation forecasts' accuracy when combined with an ANN. A modest enhancement may be made using NFL to categorize the cloudiness indices depending on the humidity level, temperatures, rainfall, irradiation, and time of day. Utilizing MATLAB Simulink, the features of a solar PV array have been examined. In terms of accuracy and error metrics, the study's findings were compared to those of other traditional methods. The test's findings demonstrate that, in comparison to previous approaches, the suggested NFL-ANN model successfully forecasts solar radiation in a variety of climatic situations. This is because, in contrast to empirical studies, this approach may take a wide range of input variables, strengthening its dependability. To increase forecasting accuracy, further research will create a more thorough optimization approach with an ANN model and employ a larger dataset to train the ANN approach.

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