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Anuradha Tomar
Prerna Gaur
Xiaolong Jin *Editors*

Prediction Techniques for Renewable Energy Generation and Load Demand Forecasting

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Prediction Techniques for Renewable Energy Generation and Load Demand Forecasting

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Preface

The intermittent nature of renewable energy generation acts as a barrier to renewable energy implementation; therefore, renewable energy generation and load prediction become a very interesting area of research. This book gathers a wide range of research on techniques for renewable energy generation and load forecasting. This book not only covers the generation forecasting techniques but also has a separate section for load forecasting. It includes systematic elaboration of the concept of intelligent techniques for renewable energy and load forecasting. The book reflects the state of the art in prediction techniques along with the worldwide perspective and future trends in forecasting. It covers theory, algorithms, simulations, error, and uncertainty analysis. It offers a valuable resource for students and researchers working in the fields of sustainable energy generation and electrical distribution network and prediction techniques. The state-of-the-art techniques in the areas like hybrid techniques, machine learning, artificial intelligence, etc., are included in an effort to present recent innovations in the prediction techniques for renewable energy generation and load forecasting. The research work shared helps the researchers working in the field of renewable energy, load forecasting, generation forecasting, power engineering, and prediction techniques and learns the technical analysis of the same.

The book covers two sections: renewable energy generation forecasting and load forecasting. In the first chapter "Introduction to Renewable Energy Prediction Methods" deals with the introduction to renewable energy generation prediction. It discusses the renewable energy status across the world and possible ways to achieve zero-carbon energy systems and intelligent techniques to achieve efficient generation forecasting. In the second chapter "Solar Power Forecasting in Photovoltaic Modules Using Machine Learning" includes solar power forecasting using ML techniques. It covers different models for the solar power forecasting. In the third chapter "Hybrid Techniques for Renewable Energy Prediction" covers the hybrid techniques for renewable energy prediction. It includes different hybrid methods for hydropower prediction, wind power prediction, and solar power prediction. Deep learning technique for renewable energy prediction is discussed in the fourth chapter "A Deep Learning-Based Islanding Detection Approach by Considering the Load Demand of DGs Under Different Grid Conditions". It includes deep learning-based islanding detection technique. A comparison of PV power estimation methods has been discussed in the fifth chapter "Comparison of PV Power Production Estimation Methods Under Non-homogeneous Temperature Distribution for CPVT Systems". In the sixth chapter "Renewable Energy Predictions: Worldwide Research Trends and Future Perspective" includes worldwide research trends and future perspective for renewable energy generation. In the seventh chapter "Models of Load Forecasting" provides an overview and elaborates on the concept of load forecasting and different models and state-of-the-art techniques for load forecasting. It also discusses identified benefits and challenges/barriers to their further development. It includes the operational issues and key challenges related to load forecasting integrated with local grid. In the eighth chapter "Load Forecasting Using Different Techniques", the future load is predicted with the help of artificial intelligence techniques, namely fuzzy logic, ANN, and ANFIS. All three methods are used for the data set considered, and the results are analyzed. In the ninth chapter "Time Load Forecasting: A Smarter Expertise Through Modern Methods" discusses time load forecasting. It provides an extensive review on the classical methods as well as modern techniques for load forecasting. In the tenth chapter "Deep Learning Techniques for Load Forecasting" explains the deep learning techniques for load forecasting from a range of perspectives. This chapter includes the load forecasting solutions that can address the key challenges. This work shared helps the readers in improving their knowledge in the field of power engineering and state-of-the-art forecasting techniques and learns their technical analysis. Each chapter provides a comprehensive review and concludes with a case study for better understanding of the reader. By following the methods and applications laid out in this book, one can develop the necessary skills and expertise to help have a rewarding career as a researcher.

New Delhi, India — Anuradha Tomar
New Delhi, India — Prerna Gaur
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Introduction to Renewable Energy Prediction Methods

Saqib Yousuf, Junaid Hussain Lanker, Insha, Zarka Mirza, Neeraj Gupta, Ravi Bhushan, and Anuradha Tomar

Abstract Renewable energy prediction began in the early years of the twenty-first century. As there is so much uncertainty in forecasting the renewable energy, several different approaches have been developed. The forecasting methodologies are very difficult to label because each model predicts a different set of installed and generation capabilities, cost of production, demand and supply, etc. There are several techniques used to predict renewable energy, including assessing the current situation or projecting the future while concentrating on a particular target of interest. Prediction techniques for renewable energy provide valuable information about the potential changes in the energy that will be generated in the near future. This chapter provides the various artificial intelligence techniques used for more significant prediction of renewable energy, and also their application is discussed. This includes AI for wind prediction methods, AI for solar prediction methods, and other energy prediction models such as time series models, unit root test and co-integration models, ANN models, and expert systems. These techniques are area and time dependent based on the idea that weather variables like wind direction and speed, temperature, relative humidity and solar irradiance, etc., tend to represent strong relation among areas close to one another. Accurate prediction promotes the significance of renewable energy by way of improving their reliability and making them economically feasible.

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1 Introduction

1.1 Renewable Energy Status of the World

Renewable energy has the potential to make a significant contribution to global energy security and carbon reduction. Renewable energy can help to reduce energy imports and usage of fossil fuels. Since fossil fuels are constantly depleting, they are becoming increasingly expensive depending on market prices. To overcome these concerns, renewable energy resources will be used to replace traditional energy sources. Renewable energy comes from natural resources that can be replenished in under a human lifetime without depleting the planet's resources. Sunlight, wind, rain, tides, waves, biomass, and thermal energy stored in the Earth's crust are examples of resources that are abundantly available worldwide and it cannot be damaged. Furthermore, their impact on the climate or the environment is negligible [1]. Over the last decade, renewable energy penetration into the power grid has greatly expanded. However, in 2020, a minor decline has been observed due to COVID-19 pandemic. The global demand for power is increased by nearly 6% and 4% in 2021 and 2022, respectively. In absolute terms, it was the highest annual rise ever (over 1500 TW). A quick economic recovery, along with more intense weather conditions than in 2020, raised the electricity demand worldwide [2].

The global electricity energy contribution is depicted in Fig. 1. Figure exhibits that low carbon sources (36.7%) contribute to about more than one-third of the global electricity and the rest (63.3%) provided by fossil fuels. Under the current climate initiatives, decarbonization of the electrical industry is a key component. As per the Paris Agreement, one of the essential indicators of climate policy is each country's nationally determined contribution (NDC). Emissions of carbon dioxide from coal fired power plants reached a new high of 10.5 gigatonnes (Gt) in 2021 with rise of 0.8

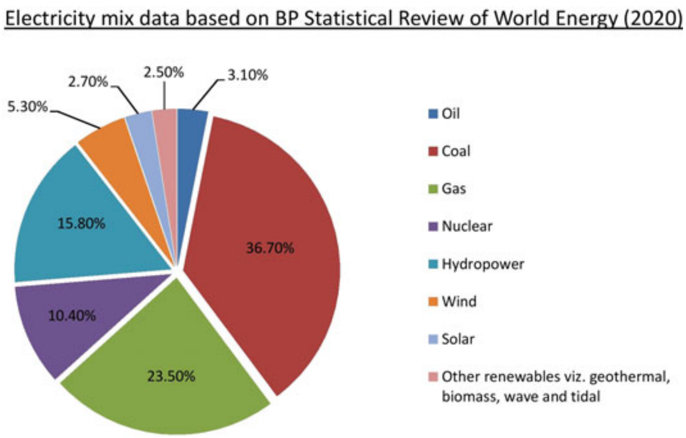

Fig. 1 Global electricity energy contribution

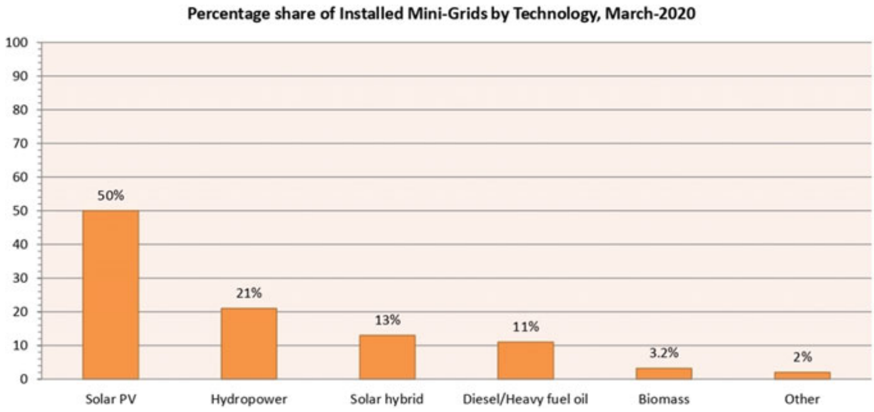

Fig. 2 Share of installed mini grids by technology

Gt as compared in 2020. Despite a surge in coal use, renewable energy and nuclear power generated more global electricity in 2021 than coal.By 2050, renewables are expected to account for 80–90% of worldwide electricity generation. Renewable energy's share of the power mix is expected to double in the next 15 years. Due to falling prices, solar and onshore wind are forecasted to account for the majority of renewable energy resources (RES) growth in 2050, accounting for 43% and 26% of total generation, respectively [3, 4].

Figure 2 indicates the share of installed mini grids by technology worldwide. It is observed that the renewable-based mini grids are increasingly being recognized as a significant booster of energy access. In March 2020, 87% of the 5,544 mini grids operating in energy access set-ups (with a total capacity of 2.37 GW) were renewable sources. Solar PV has become the fastest rising mini grid technology, with 55% of mini grids consolidated in 2019, up from only 10% in 2009 [3].

1.2 Artificial Intelligence in Power System

A power system is a complex network of generation, distribution, and transmission lines that are all interrelated. The primary purpose of power system operation and control is to provide customers with high-quality electricity at an affordable price, while also ensuring the system's stability and reliability. As the electricity system continues to expand and incorporate new technology, it has evolved into a complicated unit. There are uncertainties in real power flow due to continual load variation and increased penetration of renewable resources. Frequency fluctuations in the power system are caused by any imbalance between generated power and load demand, or by a mismatch in scheduled power interchange between areas. Artificial intelligence (AI) is defined as the intelligence demonstrated by machines and soft-

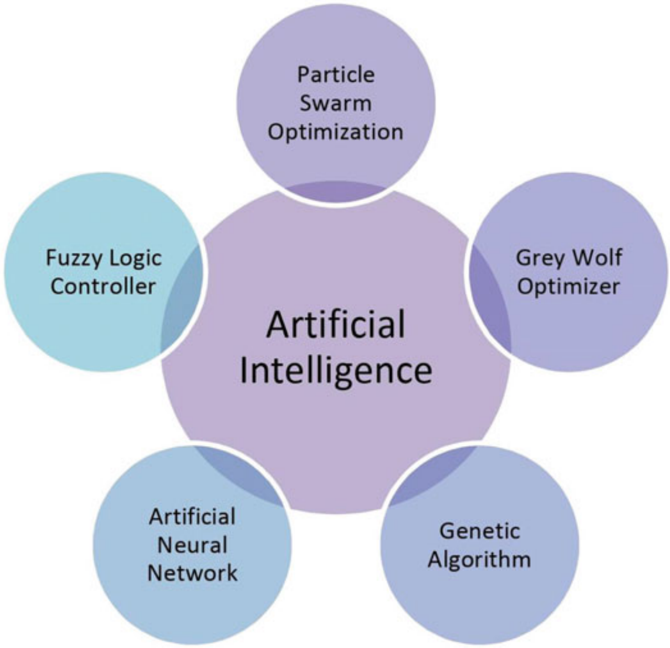

Fig. 3 Artificial intelligence in power system

ware, such as robots and computer programs. The term refers to a project aimed at building systems with human-like cognitive processes and traits, such as the ability to think, reason, find meaning, generalize, differentiate, learn from past experience, and correct mistakes. Artificial intelligence is the intelligence of a computer that can successfully complete any intellectual task that a human being can. Artificial intelligence helps in the mitigation of frequency deviations. Power systems are complicated and nonlinear, with variable loading and system characteristics that are dependent on operating points [5]. Different controlling strategies, such as conventional controllers, have been developed; however due to the presence of nonlinear components, they do not produce satisfactory results. To address the problem of nonlinearity, a few artificial intelligence techniques as shown in Fig. 3 such as particle swarm optimization (PSO), grey wolf optimizer (GWO), genetic algorithm (GA), artificial neural network (ANN), and fuzzy logic controller (FLC) have been used to determine proportional, integral, and derivative values [6]. These strategies can be used to optimize nonlinear PID controller parameters, resulting in enhanced system performance in terms of settling time, overshoot, and undershoot [7].

The scale of the power system will continue to grow in future, as will its complexity, which will bring some more difficult factors to deal with, where some artificial intelligence currently has their own set of advantages, disadvantages, and limitations. Artificial intelligence will improve in terms of maturity and ease of use, allowing it to better tackle problems in power systems. In a nutshell, combining a number of technologies with artificial intelligence will be a prominent trend in future development.

1.3 AI for Wind Energy Prediction

With the increase in the consumption of energy and due to depletion of available conventional energy resources, it has become imperative to harness the renewable sources of energy, one among which is wind energy. As per the precursory statistics published by World Wind Energy Association (WWEA), the capacity of wind turbines has reached a record of 975 GW in 2021 in the world market. One of the challenges to integrate the wind energy into the grid is the uncertainty, i.e. generation is intermittent and uncontrollable. Therefore, to predict future generation from wind is important so as to meet the demand as generation varies. The factors to be considered for a desired output from wind energy include climate change, wind reduction, fluctuating weather events, wake turbulence, etc. The evolution of global cumulative and annual installed wind power capacity(GW) during 2001–2021 is depicted in Fig. 4.

Table 1 shows the development of cumulative and annual installed wind power capacity in India over the years. The cumulative installed wind power capacity increased from 1.46 GW in the year 2001 to 40.07 GW in the year 2022. Also the annual installed wind power capacity increased from the year 2001, but there is a minor decline in the year 2020 because of COVID-19 pandemic.

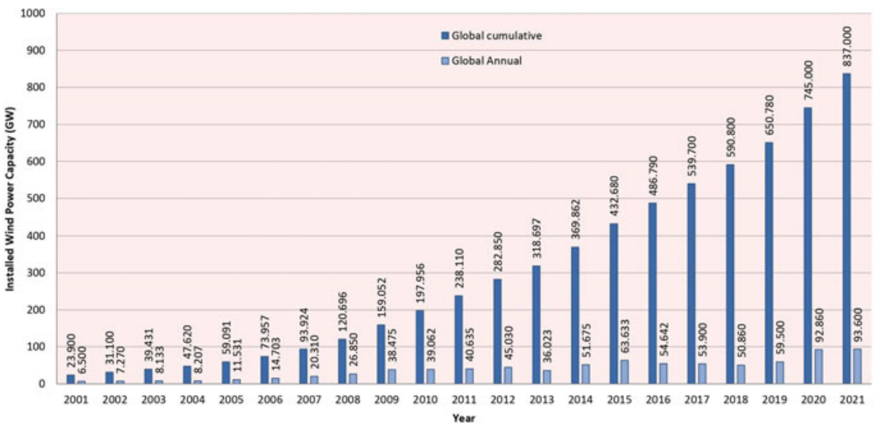

Fig. 4 Development of global cumulative and annual installed wind power capacity during 2001–2021

Table 1 Development of cumulative and annual installed wind power capacity (GW) in India during 2001–2021

Year	India cumulative (GW)	India annual (GW)
2001	1.46	0.289
2002	1.7	0.246
2003	2.13	0.423
2004	3	0.875
2005	4.43	1.43
2006	6.27	1.84
2007	7.85	1.575
2008	9.66	1.81
2009	10.93	1.271
2010	13.07	2.139
2011	16.08	3.019
2012	18.42	2.337
2013	20.15	1.729
2014	22.47	2.315
2015	25.09	2.623
2016	28.7	3.612
2017	32.85	4.15
2018	35.13	2.28
2019	37.51	2.38
2020	38.63	1.12
2021	40.07	1.44

Technologies like artificial intelligence and machine learning are turning out to be effective way to predict the wind energy and can predict the wind speed in a short period of time.

Artificial intelligence is a branch of computer science in which intelligent devices or artefacts are created and educated to behave like humans by obeying particular directions in computer programming systems. It handles huge input data and can build effective representations. AI-based forecasting models speed up decision-making, data mining, and clustering challenges. Furthermore, they can perform difficult tasks in a reasonable amount of time and without being explicitly coded [8]. Depending upon the geographical conditions, viz. wind speed, wind direction, air pressure etc., the AI-based wind prediction basic model developed is shown in Fig. 5.

Time series is analysing data collected over an interval of time and uses historical information to produce mathematical model, estimating the values and validating simulation results. A set of observation is taken at set forth time preferably at same intervals. The future values are based on the previously observed values, and the data is analysed using artificial intelligence. They may, however, fail to offer appropriate prediction results, particularly when the time series happen to be non-stationary [9].

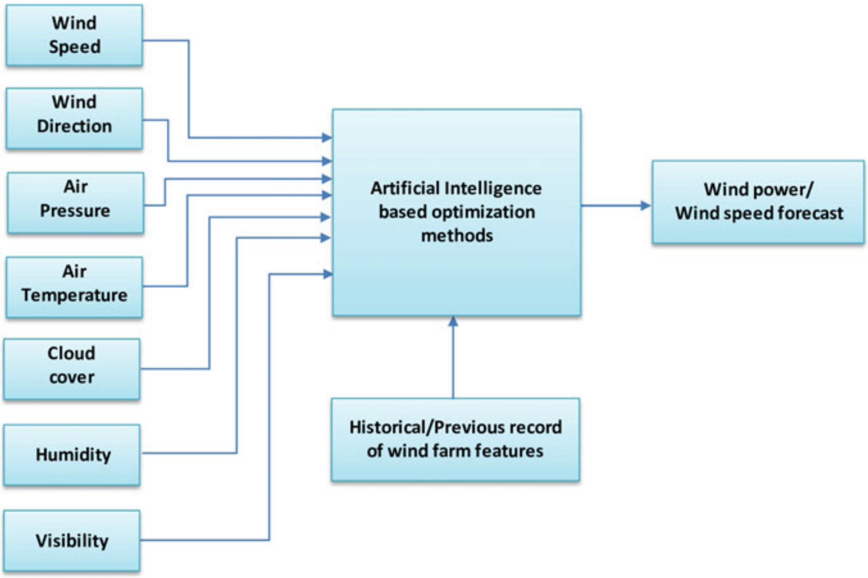

Fig. 5 AI-based wind prediction model

Deep learning program works as a function based on MLP training algorithm. Data collection is done on hourly basis during a period of 24 h taking factors like wind direction, air pressure, and the speed of wind into consideration. To produce the expected output, the data is fed to algorithm for its training purpose [10].

Artificial neural network-based AI plays a vital role in wind farm optimization and works like a human brain consisting of a big network of interconnected neurons, and this structure is replicated to get the desired results as of brain. ANN can be trained to work in turbulent conditions, and the network can be used for accurate results. Wind farm can be considered as a number of clusters with each group of turbines having identical behaviour for specific leading weather regimes. In [11], conjugate gradient descent has been used to optimize the artificial neural network model to develop conjugate gradient neural network (CGNN). While doing experiments on various scale data sets, it has been observed that the performance of CGNN increases significantly, with average iterations dropping by over 90% without compromising the accuracy of prediction. Long-term and mid-term power predictions of wind output are both well served by CGNN. The CGNN uses significantly less training time than the steepest gradient neural network (SGNN), racial basis function (RBF), and extreme learning machine (ELM).

Hybrid methods: Various methods of AI can be combined for improving overall efficiency and accuracy. Multiple algorithms are used to develop diverse predictive models [9]. When compared to single forecasting modelling methodologies, hybrid forecasting, such as autoregressive integrated moving average (ARIMA) and artificial neural network, is seen to be a potentially beneficial alternative [12].

In order to enhance wind power forecasting, a two-stage technique is also used. After decomposing wind time series with wavelet decomposition, an adaptive wavelet neural network (AWNN) technique is utilized to predict wind speed by regressing each decomposed signal hours ahead of time. A feed-forward neural network is then used to construct a mapping between wind speed and wind power output. The latter permits expected wind speed to be converted into predicted wind power. The AWNN technique provides the best approximation and training capacity when compared to a feed-forward neural network.

In [10], Bayesian optimization (BO) is used to fine-tune hyper-parameters of Gaussian process regression (GPR), support vector regression (SVR) with multiple kernels, and ensemble learning (ES) models (i.e. boosted trees and bagged trees) to improve predicting performance. In addition to this, in order to improve the forecasting performance of the analysed models, dynamic information has been added into their development.

The study uses the input as wind speed data and the output as wind power data, both obtained at ten-minute intervals over an eleven-month period. In order to predict the wind power, artificial intelligence approaches such as artificial neural networks and genetic algorithms are applied. In artificial neural networks, the genetic algorithm (GA) and back propagation algorithm (BPA) are utilized as learning algorithms. In order to obtain the finest architecture, several parameters such as learning rate, momentum coefficient and epochs are changed in back propagation algorithm. Likewise in the genetic algorithm learning approach, the crossover proportion and elite count are changed together along with various variables to pick the optimal model.

1.4 Energy Prediction Models

Techniques for forecasting can be used to augment decision-maker's management and common sense abilities. The most effective forecaster can combine a skillful combination of quantitative forecasting approaches with sound judgement avoiding total reliance of one or the other. A capital-intensive industry delivers energy with a significant lead time. The goal was to develop and make accessible to government agencies simple prediction models that catch the most important characteristics of data patterns that can be simply comprehended, applied, and have significant output potential. The various energy prediction models are as follows:

- Time series models
- Unit root test and co-integration models
- Regression models
- Genetic algorithm/fuzzy logic
- Econometric models
- Grey prediction
- Decomposition models

- Input–output (IPO) models
- ARIMA models
- ANN models and expert systems.

1.4.1 Time Series Models

The time series models use trend analysis of time series to extrapolate energy demands for the future. Time series means an ordered series of values for a variable at equal intervals of time. Traditional energy demand forecasting methods define correlations between observable factors and the desired parameter. Average temperature, total count of clients, days with high temperatures, total units of residence, price of fuels, population, per capital income of a person, manufacturing value added, index of various indicators like cost of labour in commercial activities, average price of electricity, and per cent rural population were all factored into these models. India's electricity demand is projected using time series models [13]. Time series analysis was utilized by Himanshu and Lester [14] to forecast electricity demand in Sri Lanka.

1.4.2 Unit Root Test and Co-integration Models

Vector error correction method (VECM) and co-integration approach are frequently used as the key research tools to explore the long-term relation between macroeconomic factors like refined petroleum, crude oil, liquefied petroleum gas, etc., the majority of which do not remain stationary. These two strategies were chosen for two reasons, for starters the traditional econometric techniques are plagued by false regression issues and the other reason being that the majority of economic variables utilized in the equation for energy import demand like industrial output, price, etc., are likely to be endogenous, hence predicting energy demand with a single equation may result in simultaneous bias leading to inaccurate conclusions. With the help of the VECM, both difficulties can be solved. China's energy imports are quickly increasing due to its large energy consumption, and the energy import demands of China have been forecasted using co-integration and vector error correction (VEC) models [15].

1.4.3 Regression Models

Energy prediction is crucial in the development of energy and environmental policies. Both short-term and long-term electric load forecasts are accomplished using regression models. In these models, the measure of connection between the average value of one variable (e.g. output) and the value that corresponds to other variables is used (e.g. cost and time). Economic aspects have been studied in relation to annual power consumption in North Cyprus using regression [16].

1.4.4 Genetic Algorithm/Fuzzy Logic

In recent years, soft computing technologies have been applied in energy demand forecasting. GA is the method of optimization inspired by Darwinian natural selection and evolutionary genetics that uses repeated search procedures. Fuzzy logic is a kind of variable processing that allows many true values to be processed utilizing the same variable. Fuzzy logic was utilized to forecast short-term electric power demand. The fuzzy logic methodology was used to predict Turkey's short-term annual power demand [17].

1.4.5 Econometric Models

Energy consumption is linked to other macroeconomic issues in econometric models. Econometrics is the quantitative application of mathematical and statistical models to data in order to develop theories or test hypothesis in economics and to forecast future trends based on historical data. Total energy demand for the province of Quebec was computed as a function of previous year's energy price, real income, energy consumption, and heating day [18].

1.4.6 Grey Prediction

Due to its ease of use and capacity to identify unknown systems with only a few data points, grey prediction has gained popularity in recent years. Energy demand forecasting is a grey system problem as a few characteristics like population, GDP, and income have an impact on energy demand, although the exact nature of that impact is unknown. Grey prediction is based on a theoretical examination of the original data and the production of grey models of the data in order to uncover and regulate the development laws of the system of interest so that scientific quantitative predictions about the system's future can be made. A grey prediction model with a genetic algorithm was used to forecast China's energy consumption [19].

1.4.7 Decomposition Models

Two typical methodologies for decomposition are energy intensity (EI) and energy consumption (EC). Structural change in production, change in sectoral energy intensities, and change in aggregate production level are the main defined effects that impact the EC approach, but only the first two effects are covered in the energy intensity approach. Its research covers period vs time series decomposition, the importance of different levels of sector disaggregation, result interpretation, and method selection. In 15 European Union nations, decomposition approach has been utilized to estimate aggregate energy usage [20].

1.4.8 Input–Output (IPO) Models

IPO framework is a functional graph that represents the processing tasks, outputs and inputs which are required to convert inputs into outputs. During the procedure, any storage that takes place is occasionally included in the model. The inputs indicate the flow of materials and data entering the process from outside sources. An input–output model was integrated with a growth model to explore the effects of economic expansion on energy usage in Brazil [21].

1.4.9 ARIMA Models

In energy demand forecasting, autoregressive integrated moving average (ARIMA) models are often utilized. Autoregression basically refers to a statistical model that predicts future values based on past values. It is a form of statistical analysis that employs time series data to better comprehend the data or forecast future trends. Regression models that used the seasonal latent variables generated the best results. It employed three models to estimate power demand: regression model, ARIMA, and seasonal ARIMA [22].

1.4.10 ANN Models and Expert Systems

Previously, neural networks and expert systems were extensively utilized to forecast electrical load. They have also been used to anticipate long-term energy demands using macroeconomic data in recent years. An expert system is AI software that solves problems that would ordinarily need a human expert utilizing knowledge stored in a knowledge base preserving the expertise of a human expert. A type of neural network is artificial neural networks (ANN), and it is essentially a computer simulation. It is based on the structures and functions of biological brain networks. Neural network changes are dependent on input and output because the structure of the ANN is modified by information flow [23].

1.5 AI for Solar Prediction

Carbon emissions from monetary mobility are continuing to rise, with India now ranking third among individual countries in terms of carbon emissions. Renewable energy is the way forward, and policy and technical solutions should be used to eliminate the barriers to its collection. The fundamental issue with most renewable energy supplies is that they are subject to the whims and vagaries of nature, making them a volatile and unpredictable source of energy. The system's operation is defined and determined by predicting the power from these variable power sources. This chapter presents a PV generation forecast model based on ANN and ANFIS.

Energy is essential to a country's monetary success and human prosperity since it allows living things to evolve, expand, and exist. Energy has evolved into a critical product, and any uncertainty about its source can stymie economic activities, particularly in emerging countries. In this regard, energy security is critical for India's economic success as well as its social progress goals of poverty reduction, job creation, and achieving the Millennium Development Goals [24]. Due to its present level of energy consumption, India is increasingly shifting its focus to sources of renewable energy. The Jawaharlal Nehru National Solar Mission (JNNSM), India's solar enterprise, was inaugurated to much fanfare. People who submit requests and show interest in the part will be eligible for a number of incentives from the government. The solar photovoltaic market in India grew by 75% in 2010 and half in 2011. India might become a major player in the global solar market with the correct policy support from the Indian government. Among the mission's main goals is to make India the world leader in solar energy generation by 2022, with a deployment target of 20 GW.

Solar power is abundant in India, its average annual temperature varies from 250 to 27.50 °C because its placement between the Cancer Tropic and the Equator India, as a tropical country, has a huge potential for PV power generation. India has a lot of PV power generation potential because it is a tropical country. India has an average annual solar radiation intensity of 200 MW/km^2 and 250–300 bright days [25]. India receives 5000 trillion kWh per year, according to government estimates, with 4–7 kWh per square metre every day for the majority of the country. The International Electricity Agency estimates that India would require 327 GW of energy generation capacity by 2020. Energy departments need to be able to predict the production of these renewable sources since it allows them to change dispatching arrangements in real time, boost reliability, and minimize generation system spinning reserve capacity. Solar power forecasting has received a lot of attention. Physical and statistical methods are the two types of short-term power forecasting methods for solar power plants. One of the physical strategies is to develop a physical equation for calculating solar power production methods and system attributes, as well as expected meteorological data. Statistical approaches aim to summarize intrinsic laws in order to forecast solar power using historical data. Although each of the above systems has its own set of advantages such as non-stationary state characteristics, the output of solar power has a significant impact on their characteristics and convergence [26]. Due to the Earth's rotation and revolution, solar plant output power data has a one-day periodicity from the time when solar irradiance at a place on the Earth's surface has periodicity and non-stationary features. The output power is presently increasing before noon and decreasing later.

If an appropriate solution to minimize non-stationary state features of solar output power is not applied, traditional solar power prediction methods cannot ensure the accuracy of projected outcomes or even the system's convergence. Artificial intelligence algorithms have been lauded as a viable method of forecasting solar energy production. Artificial intelligence-based systems are adaptive by nature and can handle nonlinearity. They do not require any prior modelling knowledge, and the working algorithms automatically classify the input data and match it to the proper output values. They are ‘black box’ gadgets that do not always agree on how to retain data regarding model constituents’ physical relationships [26].

1.5.1 Determination of Input Variables for the Power Forecasting Model

Accurate data on solar irradiance is usually included in a computation to predict expected output power. Weather estimates are intrinsically linked to the forecasting of renewable energy generation. A variety of environmental factors must be taken into account in order to predict the amount of solar irradiance or power generated, including solar irradiance, cloud cover, atmospheric pressure, and temperature, as well as PV panel conversion efficiency, installation angles, dust on a PV panel, and other random factors. All of these factors have an impact on the output of a PV system. As a result, while choosing input variables for a prediction model, deterministic elements that are significantly related to power generation should be considered. Furthermore, because time series data on PV power generation is substantially autocorrelated, this historical data should be employed as an input to the forecasting model [27].

In order to build a precise and consistent output power forecast model, it is required to analyse the effect variables for solar power plant output. The worldwide sun irradiation measured on the ground has a direct impact on the voltage impact of solar cells. A non-deterministic relationship’s direction and quality can be determined using the Pearson product-moment correlation coefficient or PPMCC estimation ranges from − 1 to + 1, with 1 denoting a positive aggregate relationship, 0 denoting no correlation, and 1 denoting a negative aggregate link. Under normal weather circumstances, Table 2 shows the Pearson product-moment correlation coefficient between PV production and environmental variables.

Solar irradiance and solar power output have a correlation coefficient greater than 0.8, indicating that the two variables are highly correlated, whereas solar power output and temperature have a correlation coefficient greater than 0.3, indicating that the two variables are positively and low-level correlated. A weak but negative association is seen by the humidity correlation coefficient. The link between solar energy production and wind speed is shaky [28].

1.5.2 Description of the Proposed Forecasting System

ANN and ANFIS forecast models are used to anticipate the power of a solar power plant based on past data. Inputs–outputs, network topology, and weighed node connections make up an artificial neural network. The properties of the problem are precisely reproduced by input features. Network topology selection is another important aspect of ANN design. This is done again to expand the number of hidden layers and nodes accessible for forecasting and training. The variables that were investi-

Table 2 Pearson product—moment correlation coefficient

Weather condition	Irradiance	Temperature	Humidity	Wind speed
Clear	0.966	0.322	−0.527	−0.229
Cloudy	0.891	0.441	−0.511	−0.025
Overcast	0.987	0.409	−0.478	0.125
Rainy	0.923	0.410	0.039	−0.178

gated were global horizontal irradiance, ambient temperature, global diffuse irradiance, wind speed precipitation, sunshine duration, air pressure, relative humidity, and surface temperature. To establish a new network, the global horizontal irradiance, ambient temperature, global diffuse irradiance, and surface temperature are all used. The neural network is fed using the forward back propagation (FBP) technique. TRAINLM and LEARNGDM are functions that are used to train and tune the neural network.

The mean square error is used to determine the performance measure. The first layer of the neural network includes nine neurons and calculates the output using the TANSIG transfer function. The adaptive neuro-fuzzy inference system (ANFIS) combines the best features of an ANN with the flexibility of a fuzzy system. The parameters of a Sugeno-type fuzzy inference system are identified using a hybrid learning technique. The least squares approach and the back propagation gradient descent method are used to learn FIS membership function parameters to mimic a given training data set. An ANFIS identifies and tunes the parameters and structure of a fuzzy inference system (FIS) using neural learning rules.

The ANFIS possesses a number of characteristics that enable it to excel in a wide range of scientific applications. Easy of use, rapid and accurate learning, excellent generalization abilities, superior explanation capabilities via fuzzy rules, and the ability to solve issues using both verbal and mathematical information are all appealing features of an ANFIS. The neuro-fuzzy method proposes using a neural network to build the fuzzy system, with the goal of defining, adapting, and refining the topology and parameters of the linked neuro-fuzzy network to establish the structure and parameters of the fuzzy rule base. The network can be viewed as both a linguistically meaningful connectionist architecture and an adaptive fuzzy inference system that can learn fuzzy rules from input [29].

1.5.3 AI for Other Renewable Sources of Prediction

Biomass Energy

Organic biomass is manufactured from substances obtained from living organisms. Wood, garbage, and plants are the most frequently used biomass substances utilized in order to derive energy. These creature's energy can be changed to useable energy in two ways, i.e. indirect and direct. Biomass is burned either directly to provide heat which then is turned into electricity or indirectly by converting into biofuel.

The adaptive neuro-fuzzy inference systems ANN is used to estimate transmembrane pressure when biohydrogen is being manufactured in anaerobic membrane bioreactor for bio-energy manufacturing in biochemical conversion technology production. Dielectric spectroscopy is used for the purpose of determining growth rate and also the substrate consumption in the process of fermentation. Chromatography Internet of things (IoT) is used for the purpose of monitoring the composition of biogas. ANN-GA-based combined strategy is used for controlling and analysing the influence of fermentation time. ANN-GA is used to evaluate the effect of the associated fermentative variables on the production of bioethanol. ANN-MLR is used to asses most favourable design variables of MFCs for improving performance. In thermochemical conversion technology for bio-energy production, Taguchi method is used to search for the the highest possible yield of sludge pyrolytic oil. Raman spectroscopy with deep learning is used for rapid differentiation of porous biocarbon. The bio-oil heating and the product distribution estimation of biomass rapid pyrolysis are forecasted using an ANN support vector machine (SVM). The syngas constitution for downdraft biomass gasification is forecasted using SVM multi-class random forests. Multi-gene genetic programming is used to forecast lower heating estimate and syngas composition for municipal solid waste gasification. ASPEN plus simulation is used for optimization of the process variables and the economic evaluation of manufacturing of butanol. Fuzzy model particle swarm optimization is used to make better the gasification rate and conversion of biomass gasification.

In the strategic decision-making process, it is critical to determine the resources of biomass that could be utilized successfully in manufacturing of bio-energy and assessing the potential of energy that could be derived from their wastes. For the productiveness of the said plan, it is required to take benefit from the past data. Taking into consideration this view point, quantitative information regarding land utilized for agricultural manufacturing, agricultural production amount, the aggregate of poultry and agricultural production yield has been used to solve the problem.

The aggregate of animal and agricultural wastes that could be acquired in coming time has been anticipated utilizing an AI-based prediction method called support vector regression (SVR) that takes into consideration the rate of rise in agricultural production yield to make long-term judgments. Vapnik and his coworkers proposed SVR which is actually a supervised learning approach for forecasting and modelling built from the support vector machines algorithm in the year 1996. The approach was born because of the need to distinguish between different data kinds. This method identifies the end points of two or more sets of data known as support vectors and regression line that runs through the middle of these vectors which represent the data sets. Data sets are not always distinguishable in a linear fashion. As a result, the nonlinear problem is cast into a high-dimensional space, and the problem's optimal function is resoluted and linearly stated using kernel functions. Kernel functions are radial based of linear form, quadratic form, and cubic form [30].

Geographic Information System (GIS) was used to determine the spatial distribution of biomass energy resources and cultivable lands. Under different scenarios, the energy that could be acquired from agricultural wastes as a result of different agricultural items being planted on idle but cultivable areas has been assessed. Users can acquire, manage, and analyse spatial and geographical data using a Geographic Information System. GIS allows you to examine and integrate disparate data spatially by displaying it in a layered structure. GIS allows distinct raster data and vector to be indicated on same plane allowing varied analyses. With the progress in computer technology, spatial analysis has grown increasingly crucial in the design and management of biomass supply networks. The Geographic Information System (GIS) has been utilized to assess transportation network accessibility, biomass raw material availability, distribution, and population. It is also commonly used in bio-energy supply chains to display the results in order to decide plant locations, distribute sources, and construct transportation systems.

By using a scenario approach, the suggested method incorporates the uncertainties that are present in the decision-making process. The biomass potential was forecasted utilizing Geographic Information Systems (GIS), artificial intelligence, and statistical data in a novel integrated manner that has never been put forward before. This study, which is distinctive in this regard, could be adapted to many areas and countries and utilized as decision support system in various processes of decision-making. First, yearly crop output and poultry figures were predicted using the SVR technique for animal/plant raw substance resources which are commonly available/grown in area and have a significant bio-energy potential that can be extracted from their waste. The level of garbage and bio-energy potentials were determined in the next stage. Then using GIS, multiple layers were created, the region's arable lands were assessed, and their number is fixed on. Finally, the bio-energy potentials that may be obtained by adopting various agricultural scenarios were discovered.

1.5.4 Summary

This chapter discusses the recent applications of artificial intelligence in renewable energy systems, such as artificial neural networks, genetic algorithm, particle swarm optimization, expert systems, and fuzzy theory. These applications have the potential to considerably increase power system efficiency, reduce human and material resource input, and play a key role in power system security. The scale of the renewable energy in power system will continue to grow in future, as will its complexity, which will bring some more difficult factors to deal with, in which some artificial intelligence currently has their own set of advantages, disadvantages, and limitations, as well as a lack of a power system applied to the effective hybrid intelligent, i.e. seek a more suitable method for artificial intelligence processing problems in the power system that combines the advantages of AI. It is believed that in future, as research advances, AI will become more mature and easier to use, allowing it to better handle operation of the power systems. In a nutshell, combining a number of technologies with artificial intelligence will be a prominent trend in future development.

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Solar Power Forecasting in Photovoltaic Modules Using Machine Learning

Bhavya Dhingra, Anuradha Tomar, and Neeraj Gupta

Abstract As fossil fuels become increasingly scarce, the globe seeks a dependable, clean, and pollution-free energy source, thus solar power is gaining traction. This makes the analysis of solar power to be generated highly important. This chapter analyses various time series methods like seasonal auto-regressive integrated moving average with exogenous factors (SARIMAX), auto-regressive integrated moving average (ARIMA), Holt-Winters and auto-regression (AR) to forecast solar power generated in household solar panels in order to determine which method can estimate the value of photovoltaic power accurately. After applying various pre-processing techniques, it is determined that Holt-Winters method for time series forecasting in additive mode predicts the values closest to the actual values of the solar power with a root mean squared error (RMSE) score of 5.3949.

Keywords Solar power forecasting · Photovoltaic modules · Machine learning Time-series analysis

1 Introduction

Solar power is a highly efficient, pollution-free, reliable and dependable source of energy. All these characteristics make solar power an ideal source of power for both domestic and industrial applications although solar power is available in abundance in nature. It is essential to forecast solar energy predicted from the photovoltaic (PV) modules for effective management of the generated power, and this process of predicting solar power is known as solar power forecasting [1]. The easiest and fastest

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way to forecast solar power is by using machine learning to learn from the past data and generate new values based on the previous trends. A number of researches are going on in this sector to find the most efficient learning algorithm which can forecast accurate values for solar power under the given conditions. One such study is given by Wan et al. [2] which evaluates the performance of various statistical techniques for the purpose of solar power forecasting in smart grid. Huang et al. proposed a dendritic neural model (DNM)-based ultra-short-term hybrid PV power forecasting approach. This study used improved biogeography-based optimization (IBBO) to train the model, which is a strategy that integrates a domestication operation to improve the performance of traditional biogeography-based optimization (BBO) [3]. Panamtash et al. used quantile regression on top of time series models to provide probabilistic forecasts. A reconciliation was done using a copula-based bottom-up technique or a proportion-based top-down method, taking into account the coherency among numerous PV sites [4].

This chapter aims to contribute to the ever-growing field of solar power forecasting in PV cells by using various pre-processing techniques like exponentially weighed moving average, exponential smoothing, etc., and a number of time series techniques like AR, ARIMA, SARIMAX and Holt-Winters to forecast solar power efficiently.

2 Methodology

This section provides a brief description of the dataset used to train and evaluate the model, the pre-processing techniques used to improve the model's learning abilities and finally a number of time series models to forecast solar power produced per day.

Figure 1 represents the architecture used for this chapter, highlighting various time series models used to forecast the solar power produced. Initially, the raw data is converted into processed form by applying a number of pre-processing techniques. This processed dataset is later on split into two parts, for training the models and testing their performance, and finally, models like AR, ARIMA, SARIMAX and Holt-Winters are applied to determine which one is most efficient for this task.

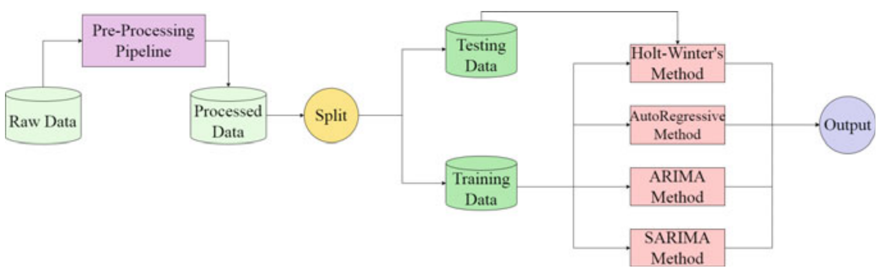

Fig. 1 Model architecture

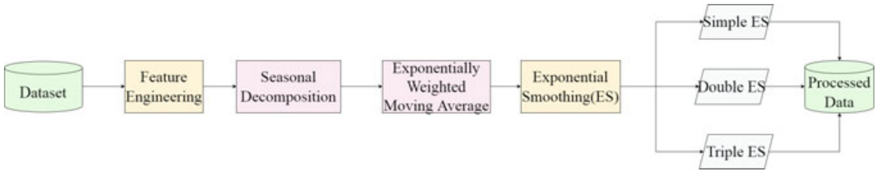

Fig. 2 Pre-processing pipeline

2.1 Dataset

This chapter is based on "Daily Power Production of Solar Panels" dataset which is an open-source dataset available on Kaggle website. In this data, 24 photovoltaic (PV) panels having a rated power of 210 W are placed at an inclination of 45 °C. These panels are made up of polycrystalline silicon. The data consists of 3304 rows and four features, which contains data, cumulative solar power consumption, daily power consumption and gas used per day. Among the 3304 rows, 2600 rows were used to train the model, whereas the rest of them were used to test the models efficiency. This dataset does not contain any null values, thus data cleaning is not required.

2.2 Data Pre-processing

In this section, various pre-processing techniques are discussed which are used in order to minimize the error obtained by the forecasting models.

Figure 2 shows the various pre-processing techniques like feature engineering, seasonal decomposition, exponential moving average and various types of exponential smoothing used before applying the time series models for the purpose of enhancing the efficiency of the models as well as generating insights from the data. These techniques are used before experimenting with the models as they add new features inside the data which are essential for the time series models to learn the trends properly.

2.2.1 Feature Engineering

Firstly, three features named day, month and year are created using date to determine the frequency and the time period of the data. After this, the cumulative values of electricity consumption and gas consumption are calculated and are added as features. Cumulative sum is estimated as follows:

$$g(x) = \sum_{i=0}^{j} x_i \tag{1}$$

In Eq. (1), x_i represents the ith row of the feature whose cumulative sum is to be calculated. Since only cumulative values of solar energy produced were given in the data, solar energy produced by day is also calculated and used as the target variable for the predictions.

2.2.2 Seasonal Decomposition

A time series can be considered as a combination of trend, level, seasonality and noise components. In this PV energy data, series is an additive model, which is defined as follows:

$$y(t) = x(t) + g(t) + s(t) + \varepsilon \tag{2}$$

Equation (2) represents a linear function which is given as $y(t)$. Variables $x(t)$, $g(t)$ and $s(t)$ represent level, trend and seasonality of the time series, respectively. ε is the noise present in the time series.

Figure 3 represents the seasonal decomposition of cumulative solar power. Since cumulative solar power is the sum of solar power produced per day, the seasonal decomposition was performed in additive mode. From this figure, it can be interpreted that cumulative solar power follows a uniform trend for seasonality and has some noise in the form of residue.

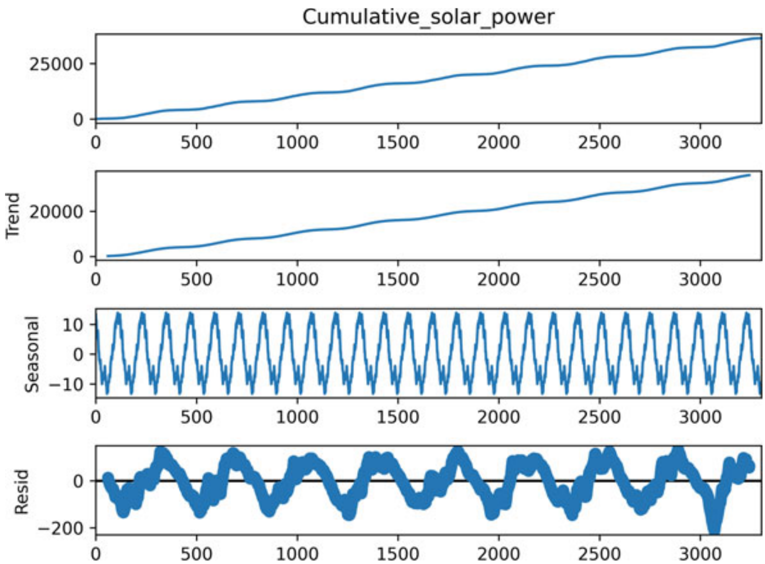

Fig. 3 Seasonal decomposition of cumulative solar power

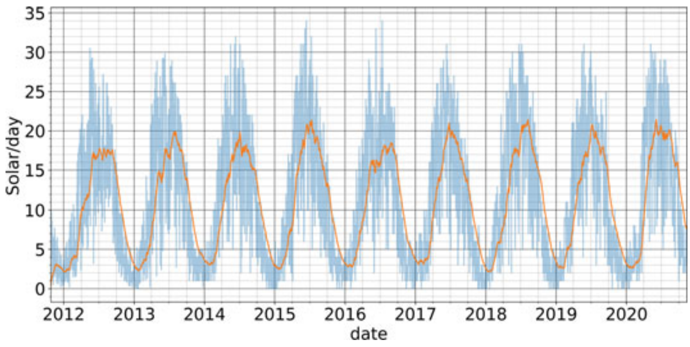

Fig. 4 Exponentially weighted moving average of solar power

2.2.3 Exponentially Weighted Moving Average

Exponentially weighted moving average (EWMA) is a statistical measure used to analyse the data points of a time series by exponentially weighting them, i.e. the weight of the older data points will fall exponentially [6]. Mathematically, this can be described as follows:

$$\text{EMWA}_t = \alpha * r_t + (1 - \alpha) * \text{EMWA}_{t-1} \tag{3}$$

Equation (3) defines a recursive function EWMA, where α is the weight used to decay the older values and r_t is current value of the time series. The effect of EWMA is seen in Fig. 4.

2.2.4 Exponential Smoothing

Exponential smoothing is a method used in univariate time series forecasting to provide support to seasonality and to handle straightforward trends in the data. EWMA and exponential smoothing are similar in some regard except that this model employs exponentially diminishing weight for prior observations, and it calculated a weighted sum of past observations [7]. Exponential smoothing is of three types:

1. Simple exponential smoothing (SES)
2. Double exponential smoothing (DES)
3. Triple exponential smoothing (TES)

SES uses a single parameter which is known as its smoothing factor (α). α is the measure of how quickly the effect of previous observations decays exponentially. SES is mathematically represented as follows:

$$l_t = \alpha y_t + \alpha(1 - \alpha) y_{t-1} + \alpha(1 - \alpha)^2 y_{t-2} + \cdot + \alpha(1 - \alpha)^t y_0 \tag{4}$$

In (4), l_t denotes the level of the series at a time t and the terms y_i are the data point of the time series. α usually ranges in between 0 and 1. When the values of α are closer to 1, it indicates that the model focuses on the most recent historical observations, while when the values of α are closer to 0, it indicates that the model considers more of the history when generating the values of PV power.

An extra smoothing factor (β) is used in DES to manage the decay of the impact of the trend shift. This provides a support for trends in time series. Based upon the type of trends, exponential smoothing can be classified as follows:

1. DES with linear trend (additive trend)
2. DES with exponential trend (multiplicative trend)

The trend equation can be represented as follows:

$$b_t = \beta(l_t - l_{t-1}) + (1 - \beta)b_{t-1} \tag{5}$$

In (5), b_t is the trend equation and l_t is the level equation at time t.

Holt-Winters seasonality method also known as TES adds another smoothing factor (γ) to manage the impact of seasonality in data. Triple exponential smoothing equation can be represented as follows:

$$s_t = \gamma(y_t - l_{t-1} - b_{t-1}) + (1 - \gamma)s_{t-m} \tag{6}$$

In (6), $(y_t - l_{t-1} - b_{t-1})$ represents the current seasonal index and the seasonal equation is used to find the weighted average of past seasonal index of m years ago and current seasonal index.

Since the data used in the chapter has trend as well as seasonality, triple exponential smoothing gives closest values to the data as shown in Fig. 5.

Figure 5 shows the effect EWMA, SES, DES and TES on the data, and from this, it can be inferred that TES has very close values to the actual values.

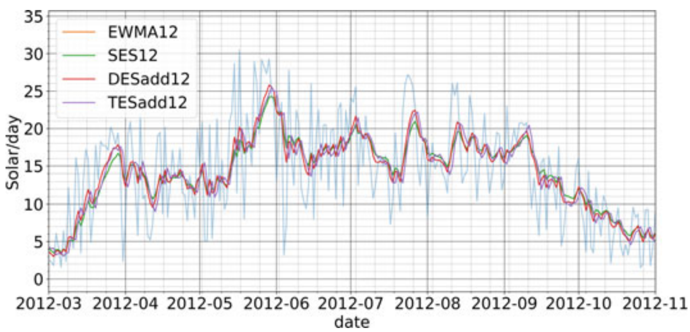

Fig. 5 Exponential smoothing for solar power

2.3 Holt-Winters Method

The Holt-Winters approach is a time series forecasting method that employs all of the level, trend, and seasonality equations. This approach has two versions depending on the nature of seasonality. When seasonality in the time series is constant, the first variant is the additive technique. The second version is the multiplicative technique, which is employed when seasonality changes proportionally to the time series level. Holt-Winter additive method is created using (4), (5) and (6) and is denoted as follows:

$$\hat{y}_{t+1} = l_t + hb_t + s_{t+h-m(k+1)} \tag{7}$$

Holt-Winter multiplicative method is expressed mathematically as follows:

$$\hat{y}_{t+1} = (l_t + hb_t)s_{t+h-m(k+1)} \tag{8}$$

In (7) and (8), k is an integer part of $(h-1)/m$. Seasonality of this dataset is constant. Therefore, Holt-Winter additive method is used to forecast solar energy produced per day.

2.4 Auto-Regression Method

AR method is another method to make time series-based predictions. This method uses previous values of the solar power produced to make the predictions for newer ones. Since it is a regressive model, it tries to fit the data in a linear manner. The general equation for this method is given as follows:

$$X(t+1) = b0 + b1 * X(t) + b2 * X(t-1) \tag{9}$$

In (9), $X(t)$ is the value of solar power at a time of t seconds. AR method makes an assumption that the previous values of the data are correlation with the future values. Thus if the values are not correlated, AR method will not be able to produce good results.

2.5 ARIMA

Another model for time series forecasting which is used for the purpose of PV power prediction is ARIMA; it forms a regressive analysis using autocorrelation in data [5]. Auto-regressive (AR), integrated (I) and moving average (MA) are the three hyper-parameters used to handle trend in ARIMA model. The ARIMA's auto-regressive component is identical to the AR model described in the preceding section. The moving average component of the model's output is similar to the EMWA described previously in that it is linearly reliant on the present and different previous observations of a stochastic factor. Finally, the differencing step to construct stationary time series data, i.e. eliminating the seasonal and trend components, is referred to as integrated. ARIMA model is useful if the data is non-stationary and is often represented by (p, d, q), where p refers to the lag in the AR model, d refers to integration order or differencing, and q is the MA lags.

2.6 SARIMAX

SARIMAX is an extension to the ARIMA model and is used to handle the seasonality of the data by adding seasonality parameters to ARIMA model and can handle external effects as well. The model is useful if the data is non-stationary and is affected by the seasonality as some time series data gets affected with the effect of seasons, and this model is able to handle such data with ease. In addition to these exogenous regressors present in this model, these variables are not affected by any other variable present, i.e. they have zero correlation with other variables.

3 Results

In order to forecast solar power generated from these PV modules AR, ARIMA, SARIMAX and Holt-Winters models were trained on 78% of the data and the remaining 38% of the data was used for evaluating the models performance. R squared, mean absolute error (MAE), mean squared error (MSE) and RMSE are the metrics used to evaluate these models.

R squared or coefficient of determination gives a statistical measure of how close the forecasted values of solar power are to the actual values of the solar power generated by estimating sum squared regression (SSR) and total sum of squares (SST). SSR is given as follows:

$$\mathrm{SSR} = \sum (y_i - \hat{y}_i)^2 \tag{10}$$

And SST is given as follows:

$$\mathrm{SST} = \sum (y_i - \bar{y}_i)^2 \tag{11}$$

From (10) and (11), R squared can be mathematically represented as follows:

$$R^2 = 1 - \frac{\mathrm{SSR}}{\mathrm{SST}} \tag{12}$$

Table 1 Time series models performance comparison

Model	R squared	MAE	MSE	RMSE
Holt-Winters	0.606	4.126	29.105	5.394
AR model	−0.049	7.194	77.590	8.808
ARIMA	−1.791	11.471	206.442	14.368
SARIMAX	−1.601	10.907	192.361	13.869

The MAE is the average of the amount of error in values of predicted solar power and actual solar power values. Mathematically, it is defined as follows:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}| \tag{13}$$

The MSE is the squared root of the average of the squared difference between projected and actual solar power levels. MSE is defined mathematically as follows:

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2 \tag{14}$$

RMSE is nothing but the squared root of (14) and is represented as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \tag{15}$$

In (12), (13), (14) and (15), N represents the number of rows in the dataset, y^i represents the actual values of the solar power, $\bar{y}_i$) is the mean value of actual values of the solar power, and $\hat{y}$ represents the forecasted values of the solar power.

Table 1 represents R squares, MAE, MSE and RMSE errors of the proposed models. From this, it can be inferred that Holt-Winters method is performing best in additive mode which is possibly due to the addition of exponential smoothing features within the data.

4 Conclusion

Power forecasting in PV cells is the process of estimating how much energy can be generated from the solar radiations. This chapter supports this task of solar PV power forecasting by applying various pre-processing techniques and machine learning models over a daily solar power forecasting dataset to find which model is best when pre-processing techniques like feature engineering, EWMA and exponential smoothing are applied to the dataset. This chapter concludes that Holt-Winter method for time series forecasting produces the most efficient results having a MAE score of 4.126, MSE score of 29.105 and an R squared score of 0.606.

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Hybrid Techniques for Renewable Energy Prediction

Guilherme Santos Martins and Mateus Giesbrecht

Abstract Due to the urgent climate change challenge and the increase in electric energy demand caused by the electrification of the transport system, renewable sources of power, such as hydro, wind, and solar, are becoming more important each day. Those sources are intermittent, and it is necessary to predict its future generation capacity to guarantee effective planning for the power system operation. The generation prediction is a time series forecasting problem, which can be solved using classical statistical methods or machine learning (ML) algorithms. Each technique presents its strengths and limitations. One can be more advantageous than the other, depending on the problem characteristics, such as the prediction horizon, the necessity to estimate the confidence level of each prediction, etc. Recently, many hybrid techniques, mixing different tools from statistical methods and ML have been developed, benefiting from the main strengths of each field to perform renewable power generation prediction. This chapter will present a detailed bibliographic review of these techniques, highlighting the recent advances in this field. An overview of hybrid techniques applied to predict time series will be presented, highlighting the most recent methods published in the literature. The following three sections will be devoted to detail the hybrid techniques already applied to predict the hydropower generation, which can be considered as one of the first renewable power sources used massively, the wind and solar power. Finally, a section containing the conclusions about the state of the art in renewable energy prediction and the future perspectives will be presented.

Keywords Renewable energy · Hydropower generation · Wind power generation · Solar power Generation · Generation forecasting · Time series forecasting

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1 An Overview About Hybrid Techniques for Time Series Prediction

Power generation prediction is an application of the most general problem known as time series prediction or time series forecasting. To handle this problem, there are many approaches, which are generally classified in three major categories: statistical, ML and hybrid methods.

The methods from the first category are based on statistical principles, such as random variables, cumulative probability functions, statistical densities, Bayes rule, among others. Roughly speaking, the derivation of time series models based on statistical methods start from a parametric model, that has its unknown parameters estimated from data with an optimization process, which is either a minimization of error or a maximization of likelihood function. The parametric model structures include auto-regressive (AR), auto-regressive with moving average (ARMA) and auto-regressive integrated moving average (ARIMA) models, where the time series is predicted based on its past values. In some cases, exogenous variables can be considered resulting into AR with exogenous variables (ARX), ARMA with exogenous variables (ARMAX) and ARIMA with exogenous variables (ARIMAX) models. Another structures commonly applied include seasonal effects, resulting into seasonal ARIMA (SARIMA) and seasonal ARIMAX (SARIMAX) models.

The main advantages of statistical methods are that the models are relatively easy to interpret and the computational burden to estimate its parameters is relatively small. On the other hand, since the methods are based on statistical concepts, many of them arise from assumptions such as linearity, stationarity, ergodicity, Gaussian nature of data, etc., which in many cases are not perfectly valid. Some relevant textbooks describing those methods are [1–3], and more recent techniques involving state space models for time series analysis can be found in [4, 5].

The ML time series prediction techniques are based on methods such as multilayer perceptron (MLP) neural networks (NN), radial base function (RBF) NN, support vector machines (SVM), artificial neural fuzzy inference systems (ANFIS), decision trees (DT), random forests (RF), heuristic optimization methods, k-nearest neighbours (k-NN), among others. Due to the recurrent nature of the problem, it also is common to find methods based on recurrent NNs (RNN) like Elman recurrent neural networks (ERNN), Jordan recurrent neural networks (JRNN), and networks based gated recurrent units (GRU) or long short term memory units (LSTM). Reference [6] provides an excellent introduction to these methods, while in [7] a more advanced discussion is provided. Many of the ML methods were initially developed for classification, but the regression problem can also be addressed adapting those tools.

The main advantage of ML techniques is a natural capacity to deal with nonlinear and nonstationary data. On the other hand, the computational burden and the interpretability of the models resultant from those methods are issues that still being discussed by the forecasting community. Furthermore, for practical cases, it was proven that in many situations those methods are not as accurate as statistical methods [8].

Hybrid techniques are interesting alternatives to pure statistical or ML time series prediction methods. Those approaches combine the advantages of statistical and ML algorithms to deal with cases where hypothesis such as linearity and stationarity are not present, and in many cases result in interpretable models with a relatively small computational effort if compared to pure ML methods. The idea of mixing different methods is present since the first forecasting competitions, such as M1, M2 and M3, where combinations of statistical techniques presented more accurate results than pure methods, indicating that the forecasting performance can be improved if more than one method is considered [9]. In M4 competition, ended on May 2018, a hybrid approach based on statistical and ML methods produced the most accurate forecasts [10]. In the most recent M competition, ML methods presented better results than hybrid methods [11, 12], but the second are still well accepted by the renewable energy prediction community.

Given the advantages of hybrid techniques, many methods were already proposed and applied to the most diverse time series prediction problems. Most of the hybrid techniques can be categorized in one of the following classes:

1. Model ensemble
   The most natural hybrid approach to forecast a time series is based on a combination of results of different methods [13]. There are two subclasses of model ensembles. The first one is the parallel model ensemble, where the input variables are given independently to different models and the final result is the combination of the outputs of each model. This combination varies from a simple mean to weighted means, with weights calibrated by optimization algorithms.
   The second class is known as serial model ensemble. In this category, input data is given to the first algorithm and the residuals are calculated by subtracting the results of this algorithm from the real data. Then, the following model is fitted using the residuals as inputs. This is repeated for all models considered in the ensemble. Generally, this kind of ensemble has two models, the first one is commonly a statistical method that predicts the linear behaviour of the time series, and the second one is a ML learning method, used to predict the non-linear components of the time series.
2. Parameters determination based on meta-heuristic methods
   Another class of hybrid methods uses metaheuristic optimization algorithms to estimate parameters of parametric models [14, 15]. In system identification problem, which is related to the time series forecasting, a similar procedure can be classified as grey box identification, since it is between the white box identification, where the system structure and the parameters are known, and the black box identification, where neither system structure nor the parameters are known [16]. The hybrid aspect in those methods is due to the mixture of a known structure, given by classical time series analysis, for example, with a heuristic optimization algorithm used to calibrate the parameters. Moreover, besides the determination of parameters in classical models, heuristic methods

can be used to estimate a set of parameters for more complex structures, such as NNs, adaptive ANFIS, among others.

3. Time series decomposition
A third approach consists on decomposing the original time series into simpler components using either structural time series theory [3], or decompositions methods such as wavelets transform (WT) [17], empirical mode decomposition (EMD) [18], singular spectrum analysis (SSA) [19], among others. After the decomposition, there are two possible approaches. In the first one, a single model with multiple inputs is trained with the different time series components. In the second one, each component of the time series is predicted using a different model, of the same nature or not, and the final prediction is the combination of the forecasts for each component [20–23].
There are many works where meta-heuristic methods are used to estimate the parameters of models obtained from different time series components. In this chapter, those references will be considered in this class, because the authors understand that the most relevant characteristic of these methods is the decomposition algorithm.
4. Other hybrid methods
Besides the three main categories identified above, there are other manners to hybridize forecasting algorithms. An example is the combination of different NNs. Another example is based on the mixture between forecasting methods and similarity-based ML methods, such as the k-NN or clustering algorithms. In that cases, the similarity methods are used to find a past moment similar to the one just before the instants to be predicted [24, 25], and then the prediction algorithm is applied based only on that part of the time series. Other works are based on combination of genetical programming (GP) and other techniques, such as variable selection methods. Since these categories are not present in all power sources analysed in this paper, these works will be categorized as other hybrid methods.

A recent review about the application of hybrid approaches for renewable power prediction can be found in [26]. In this chapter, a complementary bibliographic review will be provided, focusing on more recent articles about hydro, wind and solar power prediction and classifying the references in the categories listed above.

2 Hybrid Techniques for Hydropower Prediction

Hydropower generation capacity is related to river flow. This relates the hydropower prediction algorithms to hydrology models, that were developed since XIX$^{\text{th}}$ century. The first hydrology models were developed based on relations between rainfall and run-off, as detailed in a recent review [27]. Then, other models were developed to forecast precipitation, stream-flow, sediment, groundwater, among other variables [28].

With advances in computational capacity, data-driven methods arose. The most simple are the statistical ones, but in the current century, ML methods were deeply studied [29]. More recently, hybrid methods gained attention in hydrology forecasting community. In this section, recent hybrid techniques for hydropower prediction will be discussed, following the categories introduced in Sect. 1.

2.1 Model Ensemble

An extensive study about hydrological time series was presented in [30]. In that article, the authors performed one-step ahead predictions for a massive set of 90-year-long river flow time series from stations in North America and Europe, resulting in 599 time series. The forecasting was performed using five base methods, which were the Naive, the simple exponential smoothing, chosen for its good performance in M3-competition, the complex exponential smoothing, which was part of a competitive ensemble in M4-competition, the automatic autoregressive fractionally integrated moving average (ARFIMA) and the Facebook's Prophet. The model ensembles were all 26 possible combinations (per two, per three, per for or per five) of the base methods, and the forecast was calculated as the median of the involved methods. As a result, the authors observed that the model ensemble improved the one-step ahead performance more than any other method alone. It must be noticed that the methods used for comparison were really competitive in other scenarios, demonstrating that the model ensemble is a good strategy to deal with hydrological time-series.

Another recent work that dealt with model ensemble to predict hydrological time series was [31]. Differently from [30], where the model combination was based on the median of the results from different methods to estimate one-step ahead predictions, the authors of [31] proposed a three-phase methodology to combine the ARIMA and the Bidirectional LSTM (bi-LSTM) for long term predictions. In phase I, the authors performed a seasonal trend decomposition using loess (STL) [32] and calculated the forecast using a hybrid method based on an ensemble of ARIMA and bi-LSTM. In phase II the authors split the data to create different models for each season, decomposed the data from each season using the STL decomposition and then used again ARIMA and bi-LSTM to forecast the data for each season. In phase III an average of the two first phases was made and a final ensemble model was obtained. The authors tested the methodology both for hydro and wind power prediction data and the conclusions were that the model improved the accuracy, the uniformity and the diversity of the solutions.

In [33], different kinds of unorganized machines were used to predict streamflow from hydro power plants in Brazil. The methods were the extreme learning machine (ELM), which is a NN with random weights in its single hidden layer and output layer weights calculated with the least squares method, and echo state network, which is a NN that resembles a state space model, with a dynamic reservoir layer that represents the non-linear state transition and an output layer that consists on a linear combination of the states. Besides the networks, ensembles combining theses models and simpler ones, such as AR and ARMA were tested. Differently from the ensembles in the former references, different combiners were tested: average, median, MLP and RBF. The methods were tested to predict the streamflow for five different power plants and the ensembles were the most accurate models for one-step ahead predictions. For longer horizons, the ELM was the most accurate method.

2.2 Parameters Determination Based on Meta-Heuristic Methods

The forecasting methods described in this section to predict hydropower related variables are based on models with unknown parameters, which are determined by meta-heuristic methods. In Sect. 2.3, some of the works described also use meta-heuristic methods to calibrate model parameters. The main difference between the papers described in these sections is that the following section covers articles where some kind of time series decomposition method is applied before using the model, while the methods discussed in this section do not use any kind of decomposition.

In [34], a conceptual rainfall-run-off model, based on the physical relations between hydraulic phenomena such as precipitation, evaporation, run-off and streamflow, was used to predict the streamflow. The model had 16 parameters and its determination was considered a challenging task, due to the high dimensionality of the search space. To solve the problem, the authors used the multi-objective particle swarm optimization (MOPSO) to find a Pareto front of possible optimal solutions in the parameters space. The results were a well spread set of solutions, with greater diversity if compared to other calibration methods.

In [35], the cooperation search algorithm (CSA), which is a heuristic optimization method, was used to calculate the connection weighs and biases for neurons in hidden and output layers of an ANN trained to forecast river flow time series. The reason for applying the heuristic optimization algorithm, instead of most usual algorithms such as the back-propagation (BP) or gradient-based learning, was to avoid problems such as local convergence and slow learning rate. Many ANN structures with different combinations of inputs were tested and compared to other methods such as ELM, SVM and ANN trained with classical methods. The conclusions are that the ANN trained with the CSA algorithm outperformed the other methods with a smaller root-mean-square error (RMSE).

The Grey Wolf Optimization (GWO) was used in [36] to calibrate the parameters of membership functions in an ANFIS model to forecast the hydropower generation in a dam in Iran. The model inputs were the precipitation, the inflow and the hydropower generation in former months. The strategy was compared to the classical ANFIS. As a result, the classical ANFIS failed to produce accurate forecasts for some combinations of input parameters while the ANFIS trained with GWO was successful in all cases studied.

A similar idea was used in [37], where three heuristic methods—the particle swarm optimization (PSO), the genetic algorithm (GA) and the differential evolution (DE) were used to tune the parameters of an ANFIS to forecast the rainfall time series, which is related to flows and, consequently, to the hydro power generation capacity. The heuristic strategies were chosen due to the fact that classical parameters optimization methods may be stuck in local minima. The ANFIS with parameters calibrated with the heuristic algorithms presented better performance indicators than the classical ANFIS for models with different combinations of regressors.

Following the same idea presented in former references, [38] proposed to calculate the weighs of a classical ANN with recent physics-inspired meta-heuristics, which were the Equilibrium Optimization (EO), Henry Gases Solubility Optimization (HGSO) an Nuclear Reaction Optimization (NRO). The NNs were trained to predict the streamflow in Nile river. The accuracies of the resultant models were compared to accuracies obtained with ANN trained with classical algorithms and hybrid NNs trained with other well known meta-heuristics. As a result, the NNs trained with physics-inspired meta-heuristics outperformed the results obtained with the other methods tested.

2.3 *Time Series Decomposition*

Many hydrological time series prediction methods are based on decomposition methods. Generally, the first step consists on decomposing the time series into its components, then using a forecasting method to predict the future steps of the time series. As pointed out in the introduction either a single model with multiple inputs can be used to forecast the series or a different model can be used to forecast each component, and then, the results are combined to produce the final forecast. Both strategies are discussed here, with the ones using single models being discussed firstly.

A common method involves the time series decomposition using WT and the forecasting using some kind of ANN. The basic idea is to train the ANN with the sub-components as inputs and future samples of the time series as outputs. The idea was applied to groundwater level forecasting in [39] and to forecast hydrological time series in many posterior references, such as [40], where the classical ANN was used.

The ELM was combined with WT in [41]. In that work, the river flow time series was decomposed into a finite number of components using the WT and the past data from each component was used to train the ELM. The results were compared to the direct application of the ELM on the original time series and, as a conclusion, the hybrid method proposed reduced drastically the RMSE and the mean absolute error (MAE). The same principles were used in [42], with results better than the ones obtained with the original time series data.

Another variation associated WT with ANFIS to train rainfall-runoff models [43]. In fact, the association between the WT and ML models, such as the ones discussed above, gained attention from the hydro-climatology community since 2004, when one of the first papers combining WT and ML was published [44]. After that, many hybrid approaches following this paradigm were proposed to describe precipitation, flow, rainfall-runoff and sediment models, as pointed out in the review [45].

An idea similar to the one proposed in previous references was also explored in [46], where instead of WT, STL and SSA were used to decompose the streamflow time series. After each decomposition, three different NNs were used to forecast the time series using the components and other related series as inputs. The NNs were the convolutional neural network (CNN), the LSTM and the classical NN. As a result, six hybrid methods were developed, based on the combination of each decomposition method with each NN. Besides the streamflow time series components, the authors also used other series such as precipitation, relative humidity and temperature as potential model inputs and, in order to decide which inputs should be used in the model, the Gini index method was applied, resulting in other six hybrid methods, similar to the first ones, but with this additional feature selection step. The results of each hybrid method were compared to the NNs alone and the conclusion was that the data decomposition increased the accuracy of the forecasts. From the methods proposed, the best performance was obtained with the combination of SSA and the ANN.

For hydro forecasting, few authors proposed hybrid methods including decomposition techniques in which model is trained for each component. Some examples of that approach are discussed below.

In [47], the decomposition method was the relatively recent variational mode decomposition (VMD) [48]. Then each sub-series was predicted using an ensemble of four ML methods, which were combined using weights calibrated by solving a multi-objective optimization problem with the multi-objective grey wolf optimizer (MOGWO). Finally, the components were combined to produce the final forecast.

In [49], the runnoff data series from two stations in China was decomposed using the EMD. Then, each component was predicted using the least-squares SVM (LSSVM), which is a variation of the SVM to decrease the computational burden. To optimize the LSSVM metaparameters, a swarm intelligence method known as gravitational search algorithm (GSA) was used. Then, the results of the prediction of each component were combined and the final forecast was created. The method proposed by the authors was compared to the SVM and the ANN alone and the results showed that the hybrid method presented a substantial improvement in the root-mean squared error, demonstrating the advantages of decomposing the time series before applying the forecasting method.

2.4 Other Hybrid Methods

In [50], a hybrid method composed of three stages was proposed to forecast streamflow. The first stage was the input selection, using the least absolute shrinkage and selection operator (LASSO). The candidate input considered included many climatological indexes related to global atmospheric oscillations, sea surface temperature and rainfall. The second stage was the classification of the samples in three flow regimes: low, medium and high. The motivation for this stage was to separate data that follow three distinct patterns in order to simplify the modelling stage. Two different approaches were adopted in this stage, which were a single-variable one, in which the classes were defined based on a rainfall threshold, and a multi-variable fuzzy C-means (FCM) approach. Then, in the third stage, a different model was trained for each class. Two models were tested: a traditional ANN and a deep belief network (DBN). For the majority of the cases studied, the combination between FCM and DBN was the one that resulted in the best accuracy. The results were also better than the observed for forecasting without input selection or classification, demonstrating that the hybrid approach was relevant to enhance the models performances.

In [51], a combination between the multi-stage genetic program (MSGP) and the LASSO was used to produce relatively simple and accurate models to forecast the one-step ahead streamflow based on its past values. The idea was to use the MSGP to estimate functions between the variable to be predicted and its past values and then, to use LASSO to select the functions that were most relevant to produce accurate results. Two variants of the method were proposed. In the first one, only the functions obtained with the MSGP are considered as candidates in the LASSO procedure. In the second one, functions and some past values of the time series were considered. To compare the models both in accuracy and complexity, the Akaike Information Criterion (AIC) was used as a performance metric. The methods proposed were compared to classic GP and many SARIMA models. The results showed that the hybrid algorithm performed better considering both RMSE and AIC.

3 Hybrid Techniques for Wind Power Prediction

Wind power is a fundamental source to achieve the net zero emissions target by 2050. For this reason, the installed capacity is growing each year, with 93 GW installed in 2020 and 88 GW in 2021. Although the tremendous increase of this source penetration in electric power generation, the world needs that the installed capacity of this source grows at least 180 GW per year to achieve the emissions target by 2050 [52].

The main drawback of the wind power generation is the intermittence of wind. Differently from the hydropower, where the potential energy of water is stored in dams, there is no technical method to store the wind power directly, and indirect methods must be used, such as reversible power plants, batteries or other advanced energy storage techniques. For this reason, it is crucial to predict the winds in wind farms to plan the power dispatch.

This section describes the hybrid techniques for time series related to wind power prediction, such as the wind power itself, wind speed, wind direction, among others. As mentioned previously, the authors identified several classes of hybrid methods. In this context, the main current techniques are discussed.

Some reviews were made about wind power prediction. In [53], the status of hybrid methods for wind forecasting was described. The authors classified the hybrid methods into four fields: data preprocessing-based approaches, where some algorithm is used to decompose the time series into components easier to predict, parameter optimization-based approaches, where the parameters of a given model are optimized using some optimization algorithm, and post processing-based approaches, where the residuals of a first method are analysed using another method. In the literature review presented, several models were shown, including statistical, ML and hybrid models. The classes used by the authors of [53] are similar to the ones identified in this text, unless for parallel model ensembles, which were not explicitly classified in that work.

3.1 Model Ensemble

As for hydro power prediction, many authors explored model ensemble methods to predict wind power generation. From the many works existent in literature, some of the most recent are discussed in this section.

In [54], a meta learning-based hybrid ensemble approach for short-term wind speed forecasting was proposed. The ensemble prediction model was divided into two parts: meta-learning and individual predictor. The first part was based on a NN and the second one consists of three pre-trained individual predictors which are BP NN, LSTM and GRU respectively. The proposed model outperformed accuracy, stability and data correlation results when compared to other models such as SVM. The approach also outperformed the LSTM and NN used alone, demonstrating the advantages of model ensembles.

The authors in [55] introduced a hybrid neuro-fuzzy bootstrap prediction system for wind power generation. The bootstrap bagging technique was used to create smaller datasets from the original dataset. Each one of the smaller datasets has statistical properties similar to the ones observed in the original set. Then, a neuro-fuzzy model was trained for each smaller dataset. To forecast wind power generation, the outputs of each neuro-fuzzy model are combined by calculating the average of the results, in a parallel ensemble. The method was compared to a single neuro-fuzzy model trained with the whole original dataset and the results showed that the proposed hybrid neuro-fuzzy bootstrap method presented smaller percentage and average errors.

The authors in [56] proposed a novel ensemble model for long-term forecasting of wind and hydro power generation. The proposed model was composed of three phases. In the first phase, a hybrid model combining ARIMA and Bi-LSTM predictions was developed. The inputs to this model were the seasonal and trend components of the time series obtained using STL. The second phase is an ARIMA model with inputs defined by a Diligent Search Algorithm (DSA). This algorithm was used in order to identify hidden seasonalities of the time series. In step three, phases one and two are merged to build the final ensemble model. The method presented more accurate results than other ML and statistical methods both for hydro and wind power prediction.

In [57], hybrid serial model ensembles were developed to forecast electric power generation in a small wind turbine. The first model used in the ensemble, defined as physical model, outputs energy production using as inputs wind speed forecasts generated with a Numerical Weather Prediction (NWP) model. The second model used as inputs the outputs from the first one and other exogenous correlated variables. Many strategies were used to determine the best structure for the second model, involving naive, naive smoothing, multiple linear regression (LR), k-NN, SVM and MLP. Parallel ensembles involving those models were also considered, using different methods to combine each one of the models, such as average, weighted average, average without extreme forecasts, where the minimum and the maximum results are ignored, and ANN. As a conclusion, the most accurate method was a parallel ensemble of three methods, combined using the average without extreme forecasts. The results of this work corroborates the conclusion that a well chosen model ensemble can be more accurate than any method used alone.

In [58] a serial ensemble hybrid model composed of linear and nonlinear parts was proposed to forecast wind speed. The ensemble EMD (EEMD) decomposition technique was used to eliminate noise and reconstruct the series. Then, the ARIMA model captured the linear patterns hidden in the time series, while the BPNN model, optimized by the Cuckoo Search Optimization (CSO) algorithm, was used to forecast the residuals. The proposed model outperformed other tested methods such as ARMA alone, BPNN alone, among others.

Eight different hybrid schemes were proposed in [59] to forecast wind speed. The first step to build the ensembles consisted of input variables selection, which was made either by auto-correlation analysis or Phase Space Reconstruction (PSR). Then, the selected inputs were given to a GP or a SVM algorithm. In some of the schemes, the outputs of these algorithms were the final results. In other schemes, the residuals from the first algorithm were fed into a second model, which could be either a GP or a SVM, and then the final result was the sum of the results of the first and the second algorithms. These schemes are serial model ensembles. All four possible combinations between SVM and GP were tested as first and second models, and the other schemes were obtained by using SVM and GP alone, with each one of the two input selection algorithms. The most accurate results were provided by the combination of PSR input selection method, followed by a SVM to model the main series and the GP to model the residuals.

In [60], a hybrid ensemble approach, including statistical and ML methods, and combining series and parallel ensembles, was proposed. The first step was to preprocess data with the Kalman filter, in order to obtain a trend and a residual. The trend and the original data were given as inputs to an ARIMAX and a MLP model. The residual was treated by fuzzy-ARIMAX (FARIMAX) and fuzzy MLP. Then, the results of the two methods used to treat the trend, the two methods used to treat the residual and the Kalman filter outputs were combined to produce the final forecast. The hybrid approach outperformed other models tested by the authors, which basically consisted of parts of the whole structure used alone. In this way, the authors demonstrate that the hybrid approach used was valid.

3.2 Parameters Determination Based on Meta-Heuristic Methods

Many works were developed to forecast wind power or related variables using meta-heuristic methods to determine parameters of a given parametric model. Recently, the review [61] was published, covering the application of meta-heuristic algorithms to estimate the optimal parameters of wind power prediction models. The authors identified three layers. The first one was named as auxiliary and is responsible for decomposing the dataset into stationary subseries. The second layer was named as forecasting base, and consists of the actual forecasting model, which can be either a ML algorithm or a NN, in many of its possible configurations. Then, the third layer, named as core, is the meta-heuristic algorithm used to calibrate the parameters of the forecasting model. This framework was identified in many of the 2195 publications about wind forecasting collected by the review authors from 2011 to 2020.

In fact, the vast majority of the works related to wind power prediction that use meta-heuristic methods also use time series decomposition techniques as a pre-processing step. To maintain the classification adopted for the other renewable sources discussed in this work, all methods that include time series decomposition techniques will be discussed in Sect. 3.3. In this section, the only reference using meta-heuristic methods without decomposition for wind speed forecasting that was found is discussed in the sequel.

In [62], some wind speed forecasting techniques were proposed. In that paper, three hybrid methods were presented. The first combined Wavelet Neural Network (WNN) with Improved Clonal Selection Algorithm (ICSA), the second was a combination of WNN and PSO and lastly, the third model tested was an ELM. The series was not decomposed, as in other papers discussed. The WNN-ICSA hybrid method obtained better results in terms of accuracy.

3.3 Time Series Decomposition

One of the classes found in time series forecasting literature is based on time series decomposition. In this case, the series are decomposed into components and then, generally two different approaches are adopted: In the first one, components are used as different inputs of a single model. In the second approach, each one of the components is predicted by and individual model and the final result is a combination of the prediction results for each component. In this section, the works following the first approach will be discussed firstly, followed by references that adopt the second approach. In many cases, heuristic algorithms are used to calibrate parameters of the model used. Since the authors understand that the main feature of those works is the time series decomposition, they are discussed in this section, and not in the previous one.

In [63], the authors implemented a hybrid method using VMD, Multi-Kernel Regularized Pseudo Inverse NN (MKRPINN) and a meta-heuristic algorithm named vaporization and precipitation water cycle algorithm (VAPWCA). The VMD was used to decompose the non-linear and non-stationary time series into components, that were used as inputs to a single MKRPINN. The MKRPINN parameters were optimized using the VAPWCA. The results outperformed other models tested, which used EMD instead of VMD and other NN instead of the MKRPINN.

The authors [64] presented a wind power forecasting using a new and robust hybrid metaheuristic approach: a case study of multiple locations. This paper was developed combining Radial Motion Optimization (RMO) and PSO models. The proposed hybrid model was compared with other existing models in the literature. The results showed that the hybrid model design was more accurate than other tested models.

In [65], the decomposition method used to split the subseries was the EEMD, the forecasting model was the LSTM Enhanced Forget Gate network (LSTM-EFG) and the meta-heuristic algorithm used to calibrate the parameters was the CSO. The proposed model showed better results in terms of accuracy compared to statistical, ML and hybrids methods such as ARMA, LSTM, BPNN, EEMD-CSO-SVM and others.

In [66] a combination between WT and LSTM was proposed to forecast wind power. The WT decomposes the non-stationary time series into stationary components. Then, the components series were used as inputs of a LSTM model. The hybrid method outperformed traditional methods found in the literature, such as SVR, LSTM, WD-SVR and others.

The authors in [67] proposed a hybrid deep learning architecture for wind power prediction using as inputs the wind power and the wind speed. The data preprocessing stage was done using the EEMD. Then, the components of wind power and wind speed series, and other information related to wind direction, were processed by a bi-attention mechanism, to enhance the weights of the most significant inputs. The inputs were used to train a residual GRU, which consisted of the series association of a residual network and a GRU. Initially, the prediction model was trained using the Adam optimizer, but then a crisscross optimization algorithm (CCSO) was used to retrain the model, in order to obtain more accurate results. The proposed hybrid model outperformed in terms of accuracy and forecast stability compared to other existing models in the literature, such as persistence model, EMD-CNN-LSTM, VMD-LSTM-ELM, and others.

The authors in [68] proposed a hybrid model based on maximal wavelet decomposition (MWD), FCM, LSSVM and Non-dominated Sorting Genetic Algorithm II (NSGA-II) for short-term wind power forecasting. The MWD was used to separate the different components of the series. Then, the components were classified into three groups of similar signals using the C-means. Each group was used to train a LSSVM using the NSGA-II as optimization algorithm. The results for the proposed hybrid model outperformed other hybrid models tested such as EMD-LSSVM and WD-LSSVM, which were simple combinations of decomposition methods and the LSSVM.

In [69], a wind speed multistep forecasting model using a hybrid decomposition technique to split the time series under study into its components was proposed. Then, a deep NN (DNN) was trained using the selfish herd optimizer. The results outperformed the other models tested, which were combinations of different decomposition methods and DNNs tuned with other meta-heuristic optimization algorithms. In addition, the proposed model was suitable for wind speed prediction in several stages.

The authors in [70] implemented a short-term wind power forecasting method using the Improved Variational Mode Decomposition (IVMD) to decompose the time series and Correntropy LSTM as forecasting model. The proposed model was able to decompose the original series data, reconstruct the subseries and make wind power prediction. Differently from other methods, the LSTM parameters were optimized using non-linear analytic optimization techniques to minimize a criterion based on Correntropy loss, and not on MSE. This gives a proper treatment to outliers, that usually are present in wind speed time series. The results outperformed other traditional hybrid methods found in the literature.

The authors of [71] presented a hybrid model composed of complete EEMD with adaptive noise (CEEMDAN), Local Mean Decomposition (LMD), Hurst and BP NN. The hybrid model can decompose the wind speed time series through the CEEMDAN technique. Thus, the components obtained are submitted to Hurst analysis in order to be transformed into a series of micro, meso and macro scale. Finally, the model was applied to the prediction algorithm. The results obtained showed that the proposed model had better accuracy compared to other hybrid forecasting methods such as EEMD-Empirical WT (EWT)-BP, CEEMDAN-BP, CEEMDAN-LMD-BP and others.

The authors in [72] proposed a model based on multivariate data secondary decomposition and deep learning algorithm with an attention mechanism. The SSA technique was applied in order to reduce the noise of the original multivariate series. The multivariate EMD (MEMD) was applied in order to decompose the series without noise. The proposed hybrid model combined CNN and Bi-LSTM to extract spatiotemporal correlation features from the subseries resultant from the EMD. The results proposed model outperformed other models in precision and effectiveness.

In [73], a model to forecast wind power output using a hybrid neuroevolutionary method was proposed. The proposed method consists of three steps. In step one, the k-means model and an autoencoder are used for noise detection and filtering. In the second step, the VMD model and two heuristics called Nelder-Mead greedy search algorithm (GNM) and adaptive random local search (ARLS) are used to decompose the time series data. In the third step, a self-adaptive differential evolution (SaDE) algorithm was used to tune the parameters of a LSTM. The prediction results for the proposed hybrid model outperformed other hybrid models found in the literature, such as Bi-LSTM, DE-LSTM and others.

The authors in [74] proposed a method for one-day ahead wind speed forecasting. In that paper, a hybrid model for wind speed prediction was presented, consisting of an Adaptive GWO (AGWO), SSA and the hybrid Encoder-Decoder-Convolutional-Neural-Network-GRU Model (ED-CNNGRU). The GWO was used to tune the metaparameters of the SSA to split the series into its different components. Then, the components passed through a normalization and through the enconder-decoder network, which gave the final results after a denormalization step. The proposed model outperformed other tested models, which were a simple CNN, a simple GRU and the CNNGRU, without the ED part.

Differently from the works discussed above, in some cases a different model is trained for each component of the time series and then the results are combined. The papers where this kind of framework is adopted are discussed below:

In [75], a multi-step wind speed forecasting based on a hybrid decomposition technique and an improved BP NN was introduced. In that paper, the hybrid model was based on a hybrid decomposition based on CEEMDAN and EWT. Then, each component was predicted by a BP-NN with parameters determined with the Flower-Pollination Algorithm. The results obtained outperformed individual ML methods and other hybrid methods existing in the literature such as ELM, EEMD-GA–BP and others.

In [76], a wind speed forecasting based on WT and Recurrent WNN (RWNN) was proposed. In that paper, the proposed hybrid model was developed in two phases: in the first phase, the WT technique was used to decompose the wind speed data, and in the second phase, a RWNN was trained for each one of the subseries resultant from the first phase. The proposed model outperformed the conventional RNN model in accuracy.

A decomposition algorithm is one of the key features of [77]. In that paper, a new hybrid model for wind speed forecasting combining LSTM, decomposition methods and GWO was proposed. The dataset used in that work presented some missing data due to sensors malfunctions. For this reason, the first step of the algorithm was to fill missing data using the Weighted Moving Average method. Then, the same technique was used to smooth the data, which was normalized considering its mean and standard deviation. In the following stage, the time series was decomposed using the Improved Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise (ICEEMDAN) method. Each component was fed to a different LSTM and the results were combined using a moving average with weights determined by GWO. The method outperformed in accuracy other individual and hybrid methods.

In [78], several decomposition techniques such as WT, EMD, Empirical Set Mode Decomposition (ESMD) and EWT were used in order to decompose the time series into high and low frequency signals and also for noise reduction. A LSTM model was used to predict each component of the series and then the results of each LSTM were summed to reconstruct the forecast for the original time series. The proposed hybrid model with skip connections showed better accuracy and stability compared to other individual and hybrid models tested.

In [79], a hybrid model was introduced, which was based on combining the discrete WT (DWT) with ANN for wind speed prediction. The DWT filter was used to preprocess the time series data in order to improve the prediction accuracy. Then, an ANN was trained to predict each component of the series, and the final forecast was the combination of the ones obtained for each component. A comparison was made with popular state of the art wavelet-based algorithms and it was demonstrated that the proposed model yields better predictions results.

The authors in [80] also proposed a hybrid ML model for short-term wind speed prediction using a similar framework. The first step was to decompose the wind speed time series into several subseries using the fast EEMD (FEEMD) and PSR. For each one of the subseries, an improved whale optimization algorithm (WOA) was used in order to calibrate the parameters of an ELM. Finally, the predictions were obtained combining the predictions for each subseries. The proposed model presented the advantage of capturing nonlinear characteristics of the time series and outperformed in terms of accuracy other hybrid methods found in the literature.

Following the same framework, a parametric model and an optimization algorithm were adopted in [81] for short-term wind speed forecasting. In that paper, the time series decomposition was done using VMD, and each component was an input to a Kernel ELM (KELM), which had its weights calibrated using an improved Seagull Optimization Algorithm (SOA).

The authors in [82] proposed a method for short-term wind power forecasting. The prediction consists of three steps: wind direction prediction, wind speed prediction and wind power prediction. For each one of the steps, the algorithm detects outliers, decomposes the time series using the WT technique, normalizes the time series components and predicts the decomposed time series using the MLP algorithm. The inputs used in MLP algorithms include the time series components and other variables obtained from NWP models. Then, to reduce the number of inputs into the MLP, the NSGA-II was used to select the most relevant features. The proposed method outperformed other hybrid models tested.

Although the vast majority of wind speed or power forecasting is based on NN models, some few references use other prediction models such as ANFIS or statistical methods combined with time series decomposition. Those methods are discussed in the sequel.

In [83], a wind speed forecasting method based on SSA and ANFIS was presented. A hybrid model named SSA-ANFIS- FCM was proposed for wind speed prediction. The SSA was used to decompose the time series into periodic subseries. Then, the ANFIS model was used for wind speed prediction. The results showed that the proposed hybrid model obtained significantly reduced forecast errors compared to other models for the one-step-ahead and one-step-ahead wind prediction of 10 min.

The same first author of the previous work and other colleagues presented in [84] a new approach combining two decomposition techniques for wind speed time series decomposition: The VMD and the SSA. The decomposition techniques were combined with the ARIMA models, trained to forecast each component of the series. The proposed hybrid model was compared to pure ARIMA and presented better accuracy, precision, and stability results.

The authors in [85] introduced a hybrid approach based on DWT to forecast wind speed. This paper used physical, statistical, and artificial intelligence models for wind power prediction. The hybrid models proposed in that paper combined the time series decomposition technique, using the DWT, with statistical models, such as the ARIMA and Generalized Autoregressive Scoring (GAS). The proposed hybrid model provided better results in accuracy and complexity and it outperformed in most cases compared with existing statistical models.

In [86] a novel hybrid model based on Bernstein polynomial with a mixture of Gaussians for wind power forecasting was proposed. First, the EMD technique was used to decompose the time series and then the hybrid Bernstein polynomial-with gaussian mixing model was constructed. In order to optimize the parameters of the hybrid model, a multi-objective state transition algorithm was used. The results for the proposed hybrid model outperformed other tested hybrid models in accuracy and stability.

3.4 Other Hybrid Methods

Other hybrid methods include the combinations of statistical and ML techniques. Differently from the references discussed in other sections, neither decomposition techniques nor meta-heuristic methods were used in those papers to forecast variables related to wind power generation.

The authors in [87] proposed an approach to forecast wind power using deep learning with TensorFlow framework and PCA. The proposed model was presented to obtain the wind data hidden patterns, enhancing the wind power prediction performance. The PCA was used to extract and select the most significant features for the model. For wind power prediction, a deep learning model optimized with a TensorFlow framework was trained using the most significant input data. The proposed model outperformed other traditional methods found in the literature such as BPNN, SVM, CNN and others. No time series decomposition nor training using meta-heuristic algorithms were adopted.

In [88] a hybrid nonlinear forecasting method was proposed for short-term wind speed. The method combined Gaussian process and unscented Kalman Filter (UKF). The Gaussian process model was considered as a nonlinear transition function of a state-space model that had its states estimated using the UKF. The proposed hybrid model outperformed other tested models, such as persistence model, AR model, Gaussian process alone and some combinations of those methods, demonstrating the advantages of the hybridization adopted.

The authors in [89] implemented a short-term wind power prediction of wind farms based on the LSTM-NARX neural network. The LSTM was used to predict the wind speed based on past meteorological information. Then, the wind speed prediction was given as input to a NARX model to forecast the wind power. The results showed that the proposed hybrid model outperformed the tested methods such as NARX and WAVELET-BP.

In [90], an adaptive deep learning scheme was proposed to forecast wind speed. The idea was to use a series scheme to firstly model the data and then model the residual. To model the data, a linear approach was adopted and a search method was proposed to determine the optimal set of inputs. To model the residual, the same idea was used with a non linear method: the LSTM. Results showed that the proposed model outperformed other tested models such as statistical, ML and hybrid models.

In [91], a comparison was performed between a physical model, a NN and a hybrid model including both methods to forecast the wind power. The physical model adopted consists of the turbine power curve, which receives as input the wind speed predicted by a NWP model. The NN used many meteorological data as inputs and its outputs were the predicted wind power. The hybrid method consisted of a NN with the same inputs as the first one, plus the power predicted by the physical method. Comparisons were also made with other simpler methods, such as persistence and naive ones. As a result, the hybrid method presented better performance in almost all metrics used to perform the comparison.

4 Hybrid Techniques for Solar Power Prediction

Solar power is a fundamental source to achieve the net-zero emissions. For this reason, the global installed capacity is growing each year, with 621 GW installed in 2019 and with about 760 GW in 2020 [92].

Forecasting the electric power production capacity from this renewable source is a challenging task. This occurs because the associated atmospheric phenomena provide a probabilistic nature to solar power generation. In this context, nowadays, research studies about solar radiation forecasting attract many scholars and managers, and several models are being developed to solve that problem. These models can be classified as physical, statistical and artificial intelligence (AI). More recently, hybrid methods gained attention in the solar forecasting community.

One of the first reviews about hybrid techniques to forecast solar radiation was presented recently in [93]. The authors identified 6 categories for hybrid methods, being the first one similar to the parallel model ensemble category described in this work, the second one based on similarity, the following two based on decomposition, the fifth based on evolutionary algorithms and the last one based on residual learning, which is understood in this work as a serial ensemble method. Although the review is relatively recent, many papers were published after it was made, and in this section, recent hybrid techniques for solar prediction will be discussed, following the categories introduced in Sect. 1.

4.1 Model Ensemble

Few authors explored model ensemble methods to predict solar power generation. Possibly it is due to the fact that the solar power prediction is a more recent problem, and more advanced techniques were available when these studies started.

The only recent reference found that can be classified as a model ensemble method for solar power prediction is [94]. In that reference, a hybrid model combining

SARIMA-LSTM using a stacking technique was implemented. Thus, it was possible to create a prediction model combining the advantages of different prediction models. Furthermore, in that paper, numerical text data were combined using time series and satellite images as exogenous variables in order to extract the spatial and temporal features of solar power generation. Results showed that the proposed model outperformed in terms of accuracy and precision single models such as LSTM, RF and SVR, demonstrating that ensemble models can achieve better performance than individual models.

4.2 Parameters Determination Based on Meta-Heuristic Methods

Meta-heuristic optimization methods were also applied to forecast solar power or related variables. For example, in a recent review, almost one hundred references were found regarding the use of meta-heuristic methods to optimize SVM models parameters to predict solar radiation [95]. Other recent applications, involving either SVM and other classes of models, are presented in this section.

In [96], a hybrid method was proposed for short-term photovoltaic power forecasting. The method combined GA and SVM and consisted of two techniques: classification and optimization. The SVM classified historical weather data. Then, GA was used to optimize the SVM. Moreover, in order to define the weight/cost matrix, the GA was used again. This allows a more accurate fit of validation data. Results showed that the proposed hybrid model outperformed a simple SVM model.

In [97], a method combining Salp Swarm Algorithm (SSWA), RNN and LSTM was proposed to forecast solar power. SSWA was used to optimize the LSTM model. The input variables considered in the work were solar radiation, ambient temperature, module temperature and wind speed, whereas the model output was the power of each photovoltaic (PV) system. The proposed hybrid model outperformed other hybrid models such as PSO-RNN-LSTM, RNN-LSTM and GA-RNN-LSTM in terms of accuracy and robustness.

The authors in [98] implemented a short-term global solar radiation prediction based on LSTM and GP. GP was used to perform post-processing combining the outputs of the LSTM model to find the best prediction of global solar radiation. The performance of the proposed approach was compared to the stacking technique. Results showed that the proposed model outperformed, in terms of performance and consistency, other hybrid methods using the stacking technique, such as LSTM-KNN, LSTM-SVR, LSTM-MLP and LSTM-RF, demonstrating the advantages of the meta-heuristic applied.

In [99], a deep learning scheme was proposed for short-term solar irradiance prediction. The idea was to use GA to optimize the LSTM, GRU and RNN models. Moreover, GA was used to find the most suitable meta-parameters, such as window size and number of neurons in each hidden layer. In order to pre-process the input data, the normalization technique was used. Finally, the performance of solar irradiation prediction was compared within the three NNs mentioned above. Results showed that the GRU-GA combination resulted in the most accurate model.

In [100], a hybrid model combining SOM, SVM and PSO was implemented for solar irradiance prediction. First, SOM was used to divide the input space into several disjointed regions. Then, the SVR was applied to models each disjointed region in order to identify the characteristic correlation. Finally, the PSO was used to perform the selection of parameters in the SVR modeling. Results showed that the proposed approach outperformed other models alone, such as ARIMA, LES, SES and RW, demonstrating that the parameters optimization using meta-heuristic results in more accurate models.

The authors in [101] implemented a solar radiation prediction based on RF and PSO. The inputs were several meteorological factors, such as temperature, humidity, wind speed and others. In order to obtain the optimal performance of the RF model, it was necessary to determine the optimal parameters values, and to achieve this, the PSO technique was used. Results showed that the proposed method outperformed other methods alone, such as RF, MLP and DT.

In [102], three hybrid models combining PSO, GA and DE with ANFIS were implemented for monthly global solar radiation prediction. The sunshine duration, temperature and clearness index were considered as input variables. Results showed that the hybrid model combining ANFIS and PSO presented greater accuracy and reliability if compared to other hybrid models, such as ANFIS-GA, ANFIS-DE, SVR-RBF. Moreover, it also outperformed SVR, ANFIS and KELM models alone, demonstrating once again the advantages of hybrid algorithms.

The authors in [103] implemented a daily global solar radiation prediction based on Coral Reefs Optimization (CRO) and ELM. A combination of CRO and ELM was used for feature selection. Then another ELM was trained as a prediction mechanism. In other words, the CRO-ELM was applied to select the best set for daily global solar radiation prediction, whereas the second ELM was trained to obtain the final prediction process. Results showed that the proposed method outperformed other possible hybrid models following the same framework, such as CRO-ELM-MLR and CRO-ELM-SVR. The proposed approach also outperformed the multivariate adaptive regression splines (MARS), multiple linear regression (MLR) and SVR models alone.

4.3 Time Series Decomposition

The frameworks for solar power forecasting involving time series decomposition techniques are discussed in this section. In a similar way of what has been done for other sources, references where different components are fed to a singular model are discussed firstly, and then the references where each component is predicted by a model and then the final result is computed are discussed.

In [104], the authors implemented a hybrid model using WT, PSO and SVM to forecast PV power based on meteorological information, such as solar radiation, atmospheric pressure, humidity and wind speed. In order to decompose the meteorological variables into a set of subseries, the WT technique was used. Then, subseries of the input variables were used to train the SVM. The PSO was applied to optimize SVM parameters in order to predict each solar power subseries. Finally, the inverse WT was applied to reconstruct the solar power prediction. Results showed that the proposed method was more accurate than other hybrid models such as PSO-NN, GA-SVM and PSO-SVM. The proposed approach also outperformed SVM alone, demonstrating the advantages of using hybrid methods based on decomposition.

In [105], the authors implemented a hybrid method using CEEMDAN, CNN and LSTM. The CEEMDAN was used to decompose the original time series into components. The CNN-LSTM framework was capable of extracting spatial and temporal features respectively. Moreover, it was used to predict solar radiation one hour ahead. The proposed hybrid model outperformed other hybrid models such as CEEMDAN-LSTM, CEEMDAN-SVM, CEEMDAN-BPNN and CEEMDAN-ARIMA in terms of accuracy. The approach also outperformed LSTM, ARIMA, SVM and BP used alone, demonstrating the advantages of hybrid models.

In [106], a hybrid method was proposed to forecast hourly solar irradiance. The model combined WPD, CNN, LSTM and MLP. First, WPD was used to decompose the original time series. The decomposed time series was processed by the CNN model. The outputs of the CNN models were inserted as input to the LSTM model. The LSTM outputs were concatenated into a fully connected layer. The weather variables, along with the LSTM outputs, were used as input to the MLP model. The final prediction value was the output of the MLP model. The proposed was advantageous in terms of accuracy when compared to other hybrid methods such as RNN-MLP, BP-MLP, LSTM-MLP, CNN-LSTM-MLP and WPD-CNN-LSTM. The proposed approach also outperformed BPNN, SVM, RNN and LSTM models alone.

The authors in [107] implemented a solar irradiance prediction along a navigation route based on EEMD and Self Organizing Map-Back Propagation (SOM-BP). First, the EEMD technique was used to decompose the original time series into several subsequences with various frequency bands and also to extract the data characteristics. In order to train different networks, the subsequences obtained were used as input to the SOM model and their outputs were used as input to the BP model. The final solar radiation prediction was the sum of the outputs of all sub SOM-BP networks. The proposed model outperformed in terms of accuracy when compared to other individual methods such as RBF and BP.

In [108], a hybrid model combining PCA, Discrete Fourier Transform (DFT) and ERNN was proposed for day-ahead solar prediction. DFT was used to extract frequency features from historical solar irradiance data. The PCA was used to identify the most relevant frequency features to be considered in NN model to carry out the solar radiation forecasting. The proposed method outperformed other hybrid models such as DFT-PCA-BP and PCA-BP. The proposed approach also outperformed the ARIMA and Persistence models alone.

In [109], a hybrid method was proposed for short-term PV power prediction. The model combined Bayesian Ridge Regression (BRR), Continuous Wavelet Transform (CWT) and Gradient boosting DT with categorical features (Catboost). BRR was used to select the most important features. CWT was applied to convert the chosen features into a time-frequency domain. Catboost was used for day-ahead PV prediction. Inverse CWT was applied to obtain the prediction final values. The hybrid model presented reliability which guaranteed network energy compensation and preventive maintenance planning.

The authors in [110] proposed an approach for short-term solar generation prediction using WTP, Generative Adversarial Networks (GAN) and Dragonfly Algorithm (DA). WTP was used to decompose the series into subharmonics. GAN was applied to predict solar power generation. DA was used to train the GAN model in order to improve the prediction. The proposed method outperformed other individual methods such as ARMA, ANN, CNN, GAN, SVR, RNN and Fuzzy.

The authors in [111] implemented an hour-ahead PV power prediction based on the component extraction method, GRU and scenario generation algorithm. The component extraction method was used to identify PV power time series patterns. GRU was trained based on the detection of the daily fluctuating patterns of the PV power generation. The scenario algorithm was applied to predict the linear trend data for each GRU. Linear and non-linear parts of the data were inserted into the GRU for PV power generation prediction. The proposed method was more accurate than multiple and single GRU models.

Differently from the approaches discussed before, where a single model is trained considering each sub-series as an input, other authors proposed methods where each sub-series is modelled by an individual model. The references following this strategy are discussed in the following paragraphs.

The authors in [112] implemented four hybrid models combining Wavelet Multiresolution Analysis (WMA)-MLP, WMA-ANFIS, WMA-NARX and WMA-GRNN for modelling solar radiation. The DWT technique was applied to decompose weather signals. Then, from the decomposed series, these were modeled by ANN methods and then reconstructed to estimate the original signal. In order to model the Global Horizontal Irradiance (GHI), four meteorological variables were considered such as temperature, humidity, wind speed and sunshine duration. Results showed that the hybrid model combining WMA and GRNN outperformed in terms of accuracy when compared to other hybrid models mentioned above. Moreover, this approach also outperformed ANFIS, NARX, MLP and GRNN models alone.

In [113], a hybrid prediction method was proposed for short-term PV power. The model combined SARIMA, Random Vector Functional Link (RVFL) and Maximum Overlap Discrete Wavelet Transform (MODWT). The MODWT was used to decompose the time series. The SARIMA and RVFL models were used to predict each component of the original time series. The results from SARIMA and RVFL were linearly combined using the convex combination method in order to improve the prediction for each component, in a kind of model ensemble technique. The final forecasting was the sum of the decomposed forecasts. Results showed that the proposed hybrid model outperformed hybrid algorithms where only one of the forecasting methods were used to predict each component (MODWT-SARIMA and MODWT-RFVL) and other simpler algorithms, such as Persistence, SARIMA, RVFL and SVR models alone, demonstrating the advantages of hybrid models combined with time series decomposition.

The authors in [114] proposed an approach for short-term PV power using Wavelet Packet Decomposition (WPD) and LSTM. The WPD technique was used to decompose PV power time series. Linear weighting method was used in the decomposed series in order to improve the prediction results. Then, to predict each one of the components, a LSTM was trained considering weather data as inputs. The final forecasting value was obtained combining the results from each LSTM. The method was more accurate than LSTM, GRU, RNN and MLP models alone. The proposed approach also outperformed other hybrid methods.

In [115] a hybrid model combining MODWT and LSTM was proposed for PV power prediction. First, MODWT was used to decompose the original historical data into components. LSTM was applied to forecast each component of the PV power time series. The final value of the prediction was the weighted contribution of each LSTM. Results showed that the proposed hybrid model presented more accurate results than a DWT-LSTM hybrid model, which is an algorithm composed by a time series decomposition using DWT followed by a prediction step using LSTM. The proposed approach also outperformed LSTM, RNN, GRU and neuro-fuzzy models alone, demonstrating that the decomposition was useful to improve the prediction results.

Differently from the works above, where the same model is used for each component, the authors in [116] implemented a hybrid model using VMD, Deep Belief Network (DBN) and ARMA for solar power prediction. First, VMD was used to decompose the original historical data into components with different frequencies. DBN was applied to predict high-frequency components, whereas ARMA was used to predict low-frequency components. The proposed method outperformed other hybrid methods using the same structure such as EMD-ARMA-DBN, EEMD-ARMA-DBN, DWT-RNN-LSTM. The proposed approach also outperformed ARMA, DBN and RNN models alone.

4.4 Other Hybrid Methods

Other hybrid methods include the combinations of deterministic, statistical, ML and clustering techniques for solar irradiation or solar power forecasting. The frameworks proposed in those methods are significantly different from the other methods studied, and for this reason, are not described in previous sections.

The authors in [117] proposed an approach for solar and wind power prediction using post-processing techniques and principal component analysis (PCA). The basic data consists of solar irradiance and wind power measured by arrays of sensors scattered along large areas and predicted using NWP models. To reduce the amount of input data, the PCA technique was used. Then, the NN and Analog Ensemble (AnEn) were used as post-processing techniques. The first one provides deterministic forecasts and, the second, probabilistic predictions. The results obtained showed that combining PCA with post-processing techniques outperformed when compared to implementing using NN and AnEn directly on all prediction data, that is, without dimension reduction using PCA. Moreover, the proposed method computationally reduces the cost and prediction error, demonstrating the advantages of using data reduction techniques on large data.

Another paper where signals from multiple solar plants were considered was [118]. In that work, a hybrid model combining residual network (Resnet) and LSTM was implemented for short-term solar irradiance prediction for twelve neighbour solar plants in the same state of US. The method was compared to another hybrid method developed with a combination of Resnet and MLP and presented superior accuracy. The method also outperformed CNN, LSTM, and Resnet models alone, demonstrating the advantages of the hybrid approach.

Another combination between NNs to forescast solar power was presented in [119]. In that paper, a hybrid model combining attention-based long-term and short-term temporal neural network prediction model (ALSM), CNN, LSTM and multiple relevant and target variables prediction pattern (MRTPP) was proposed to predict hourly PV power. Results showed that the proposed method outperformed a CNN-LSTM hybrid method and simpler methods such as ARMA, ARIMA and LSTM alone.

The authors in [120] implemented a solar irradiance prediction based on satellite image analysis and a hybrid model combining exponential smoothing state space (ESSS) and ANN. The self-organized maps (SOM) technique was used to classify and detect the cloud cover index and ESSS was applied to predict the cloud cover index. Finally, the MLP model was used for solar irradiation prediction. Results showed that the proposed method outperformed in terms of accuracy when compared to other individual methods such as ARIMA, Linear Exponential Smoothing (LES), Simple Exponential Smoothing (SES) and Random Walk (RW).

The authors in [121] proposed a hybrid model using ARIMA and ANN for daily global solar radiation prediction. ARIMA was used to evaluate linear aspects. ANN was applied to model the residuals of the ARIMA model. Results showed superior accuracy when compared with ANN and ARIMA models alone, as expected. The approach was similar to the one used in [122] years before.

The authors in [123] proposed a hybrid model combining LSTM and Gaussian Process Regression (GPR) for short-term solar power prediction. LSTM was used for point solar prediction whereas the GPR method was used to estimate the confidence levels of the estimates. This was one of the few articles identified where the authors propose a probabilistic forecasting for solar power.

Differently of what was found for hydro and wind power prediction, for solar power prediction, many similarity based methods were devoped. Some examples are detailed in the sequel.

The authors in [124] implemented an hourly solar radiation prediction based on the Mycielski and Markov model. The Mycielski based model groups the solar radiation data in a matrix and then finds the submatrix patterns most similar to the last recorded value. Then, Markov model was applied in order to reflect the probabilistic relationships of the data. Results showed that the proposed model outperformed other models such as ARIMA, ANN, and a hybrid method composed of a combination between Cloud cover index and ARIMA.

In [125], a hybrid method was proposed for short-term power prediction. The model combined K-means, Gray Relational Analysis (GRA) and ERNN. In that work, weather variables and historical datasets were considered. K-means was used to group the similar meteorological factors. GRA was used to obtain the past day most similar to the day to be forecasted. Then, ERNN was applied to make the predictions into each group of days. The proposed method outperformed other hybrid methods such as GRA-BPNN, GRA-RBFNN, GRA-LSSVM and GRA-ERNN. All those methods did not have the clustering strategy adopted in the hybrid method proposed, demonstrating the advantages of similarity techniques. The approach also outperformed the LSSVM, RBFNN, BPNN and ERNN models alone.

The authors in [126] implemented an hourly solar radiation prediction based on Deep Time-series Clustering (DTC) and Feature Attention based Deep Forecasting (FADF). DTC was used to group time series into similar patterns in the same cluster. FADF was applied to predict hourly solar radiation from each cluster that was grouped by the DTC model. Results showed that the proposed method was more accurante than other hybrid models such as FADF–k-means, FADF–FCM and FADF–Gaussian Mixture Model (GMM). The proposed approach also outperformed the FADF model alone.

5 Conclusion and Future Perspectives

The many references about renewable energy forecasting in the last few years demonstrate that this topic is important and relevant. With the increase of penetration of intermittent power sources in national grids, and the increase in electrical power demand due to current trends, such as electric cars, it is possible that the number of people dedicated to this theme grows more and more each year.

Although the recent advances made by many researchers, this review, including three different renewable power sources, demonstrates that some trends observed to forecast a power source are not commonly used for the other ones. For example, although some hybrid methods containing similarity techniques are found for solar power, almost no reference for hydro or wind power can be found using this kind of technique. Another interesting observation is that most of the references for wind power prediction use decomposition methods, whereas it is not a common practice for solar or hydropower prediction. Thus, it seems that the different renewable sources forecasting communities would benefit from knowledge exchange.

Furthermore, some questions remain open. Generally, the authors that propose hybrid methods compare the results of their proposals to parts of the hybrid scheme developed. Sometimes, the complexity of hybrid methods results in marginal accuracy gains, and the authors claim that the proposed hybrid method is better, considering just the final result and not the method complexity. As the AIC or BIC criteria existent for statistical methods, a generalized criterion could be proposed for hybrid methods.

Another open question is the prevalence of point prediction instead of probabilistic predictions. While most of the techniques result only on the average of the predicted series, it is essential to know the confidence level of the predictions to solve many planning problems. State-space statistical models can provide probabilistic predictions, but this ability was lost in ML methods. An important research direction is to answer how ML methods can make probabilistic predictions.

In conclusion, even with the vast quantity of works related to renewable energy prediction, there are still many works that the community can develop about the theme.

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A Deep Learning-Based Islanding Detection Approach by Considering the Load Demand of DGs Under Different Grid Conditions

Gökay Bayrak and Alper Yılmaz

Abstract Islanding detection is a very important issue in the integration of renewable energy systems with the grid. In recent years, especially artificial intelligence and deep learning-based islanding detection methods have come to the fore in terms of providing reliable power quality. In this study, a deep learning-based islanding detection approach by considering power quality and load demand problems is proposed. It is aimed to effectively detect the islanding condition which occurs as a result of unintentional disconnection of distributed generation (DG) systems from the grid. In the proposed approach, a deep learning-based islanding detection method is developed, taking into account the faults and power quality events occurring on the load side like considering asynchronous motor startup, capacitor switching, etc., conditions that are not possible to easily detect by conventional islanding detection methods. With the developed method, it is seen that the islanding event can be distinguished from the power quality events that occur on the grid, even under noisy signals. In this way, the power quality of the grid is increased and the performance of the DG in dynamic load behavior is developed.

Keywords Deep learning · Islanding detection · Distributed generation · Artificial intelligence · Load demand

1 Introduction

Today, limited fossil fuel sustainability, environmental concerns, and increasing energy demand are universal issues that are widely addressed to find appropriate solutions. Renewable energy (RE)-based distributed generators (DGs) such as photovoltaic (PV), wind, hydrogen, etc., based DGs and electric vehicles (EVs) with

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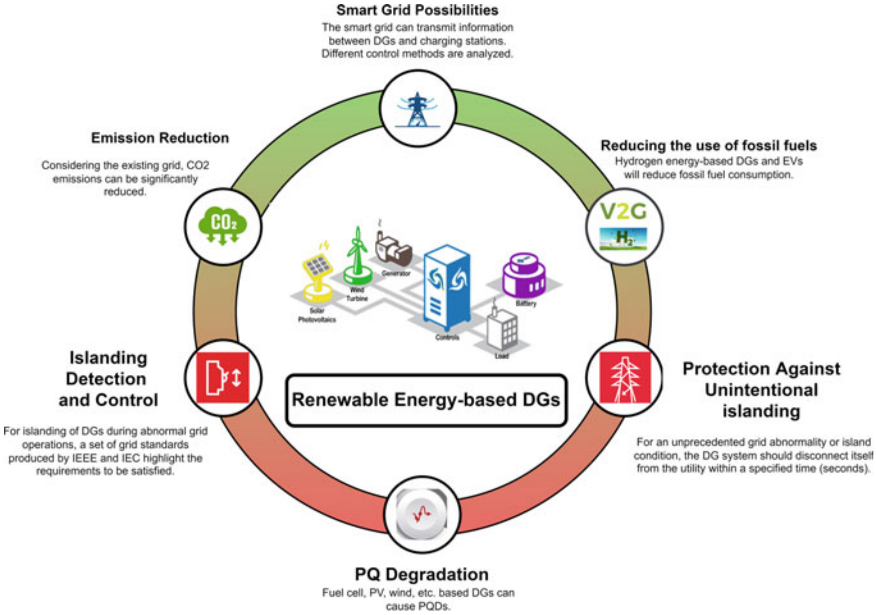

Fig. 1 Positive and negative effects of distributed generators on the main grid

vehicle-to-grid (V2G) support stand out in solving these problems [1, 2]. Figure 1 shows the positive and negative effects of these rapidly increasing systems on the grid. Here, it is an important criterion to connect the RE-based DGs and EV charging stations (EVCS) with V2G technology to the grid following the grid code requirements [3, 4].

Sustainable power flow is required for both the consumers and the grid side to provide a reliable grid integration. One of these criteria and the most important is islanding detection. Islanding as defined by IEEE 929-2000 standards [3]: The condition in which a distribution system becomes is electrically isolated from the grid yet continues to be energized by one or more local DG through the associated point of common coupling (PCC). Islanding condition in a microgrid causes serious damage to both the DG and the operator. Thus, the detection of islanding in time is an essential issue for a DG system.

In case any voltage and frequency value occurring in the grid exceeds the acceptable limits, the DG system should be physically isolated from the grid as soon as possible and continue to feed the local loads. From this point of view, there is a need for methods that can detect the islanding condition of the DG system within the periods specified in the standards from the moment it occurs [3]. Besides, the identification of islanding conditions and non-islanding events is also of great importance. In microgrids, switching of different load/capacitor groups, different DG operating conditions, and short circuit faults cause minor disturbances called power quality events (PQE) that are not islanding events [5]. Here, evaluation of DG load demand

Table 1 Islanding condition detection standards

Parameters	IEEE Std. 929-2000	IEEE Std. 1547-2003	IEC 62116
Frequency range	$59.3 \leq f \leq 60.5$ Hz	$59.3 \leq f \leq 60.5$ Hz	$f_0 - 1.5$ Hz $\leq f, f_0 + 1.5$ Hz $\leq f$
Voltage range	$0.88 \leq V \leq 1.10$	$0.88 \leq V \leq 1.10$	$0.85 \leq V \leq 1.15$
Quality factor	2.5	1	1
Detection time	$t < 2$ s	$t < 2$ s	$t < 2$ s

in different grid conditions and performing tests in all possible load case scenarios are essential for system reliability and sustainability [6]. The frequency and voltage range allowed in the standards and the island detection time are given in Table 1.

Islanding detection methods can be classified as remote, local (passive and active), and intelligent methods. However, passive and active methods have several drawbacks, including difficulty in determining a threshold value, uncertainty due to operating conditions, and susceptibility to noise [7]. Also, they contain a large non-detection zone (NDZ) [1]. The NDZ indicates the area where islanding occurred but could not be detected. Islanding detection should be possible even in the worst case where the active and reactive power generated in the microgrid is completely consumed by the loads. For good islanding detection, the NDZ should be as low as possible. NDZ is low in remote methods, but the cost is quite high [8]. To overcome the limitations of traditional methodologies, intelligent methods using signal processing and classifiers are presented [6]. Intelligent islanding detection approaches are including three steps in the literature: signal processing [9], feature selection [10], and classification [11]. In some studies in which signal processing-based techniques are applied, very high accuracy is obtained in noise-free conditions, while it is observed that this accuracy decreased in high noise conditions [6]. In classifiers, features must be correctly defined by users. Besides, the feature selection takes a long time. Deep learning (DL) methods have automatic feature extraction capability and eliminate human involvement, and it has closed-loop feedback. These methods can automatically extract features without the need for any conventional signal analysis method.

When the literature studies are examined, an effective islanding detection method should have the following features [9]:

- It should be applicable for distributed generation systems with different characteristics.
- Islanding conditions and non-islanding PQE events should be extensively tested considering the DG load demand.
- Minimum measurement parameters should be used.
- It must be validated with a large-scale dataset.
- Cost should be reduced by using a limited number of measuring devices.

In this study, a DL-based islanding detection method using long short-term memory (LSTM) and convolutional neural network (CNN) is proposed for the classification of islanding and PQEs such as sags, swells, and frequency deviations in

DG-based microgrid considering the DG load demand. The NDZ is almost zero, and the detection time is under the IEEE Std. 929-2000, IEEE Std. 1547-2003, and IEC 62116 standards. In Sect. 2, information about the mathematical and simulative data generated for islanding and non-islanding events (PQEs) is given, and the test system and data acquisition hardware are discussed in detail. In the next section, signal analysis and machine learning (ML)-based methods are discussed in detail, after briefly mentioning the conventional passive, active, and remote methods. Besides, in Sect. 3, deep learning methods used in fault detection, especially in microgrids, which are gaining popularity, are discussed. Section 4 covers the theoretical background of the proposed method, its application, and the results obtained from the method. The proposed methodology for the classification of islanding/non-islanding events is investigated by considering the DG load demand under different grid conditions. Discussion and conclusion are presented in Sect. 5.

2 Data Generation and Test System

2.1 Data Generation Using Mathematical Models and Simulation Models

Islanding events and PQEs are generated using mathematical models, simulation studies, and real data acquisition systems with an experimental setup. In this study, mathematical PQE data is generated using the integral-based method [12], following IEEE 1159 standards, with the software created in the LabVIEW environment. Researchers have the option to configure such as the number of samples, the sampling frequency, the fundamental frequency, and the normal amplitude of the signals. Figure 2 shows the LabVIEW interface of the software using the integral-based method. PQE data parameters selected inf Ref. [8, 12]. 1000 samples are generated for each event.

Simulation models are the ability to provide hundreds of different operating conditions in the computer environment that did not occur in the real system but can be realized in simulation. Islanding condition signals and PQEs are generated according to the references [9, 12] using the MATLAB/SIMULINK model. Simulations are generated for all scenarios that will occur depending on the situation on the demand side. The dataset scenarios used in islanding detection are shown in Fig. 3. The active/reactive power change in the PCC should be set to zero as specified in the IEEE 1457 standard. In this case, the variation between voltage and current values will drop to almost zero before and after the islanding [1]. The method to be proposed for the islanding detection should also be able to accurately detect the island study even in these cases. In this study, data is generated by considering various power values with low NDZ between production and consumption for islanding conditions.

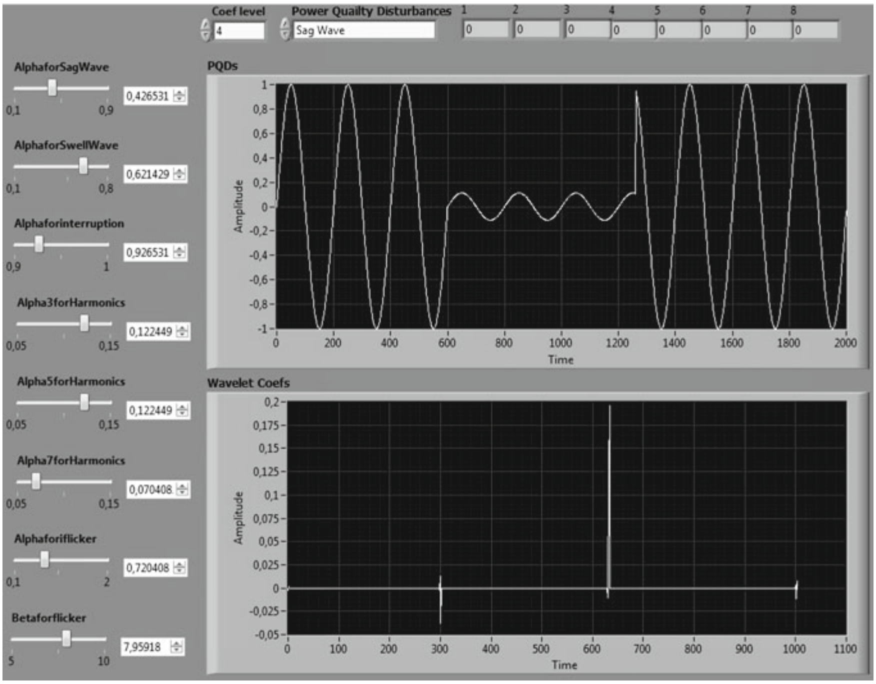

Fig. 2 LabVIEW interface of the software using the integral-based method

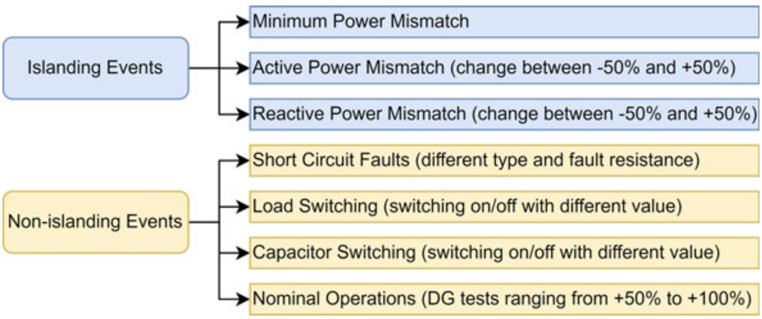

Fig. 3 Dataset scenarios used in islanding detection

2.2 Islanding Test System

The islanding detection test system following IEEE 929-2000 std is shown in Fig. 4, and the DG system operated under power factor is $Q_f = 2.5$ at the resonance frequency ($f_{\text{resonance}} = 50\,\text{Hz}$) [13]. In the applied methods, it is aimed that the detection time is below the IEEE 929-2000 standards and the NDZ is almost zero.

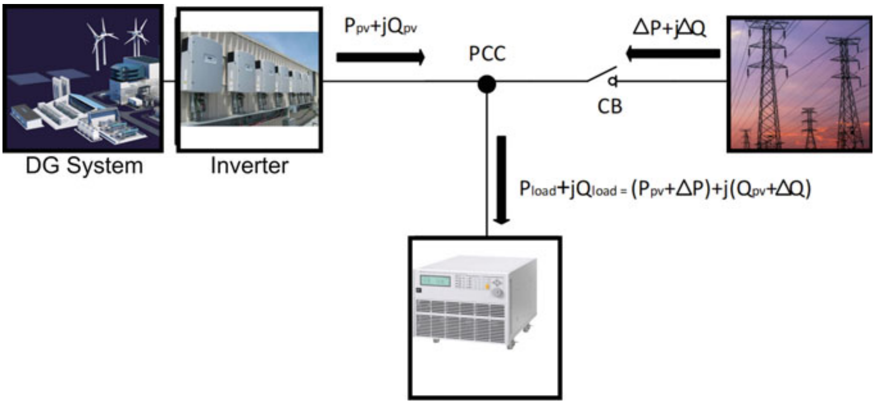

Fig. 4 Islanding detection test system

The test system is operated under a parallel load of $R = 50\ \Omega$, $L = 63$ mH and $C = 0.16$ mF. The quality factor (Q_f) for demand side load is 2.5.

$$Q_f = R\sqrt{\frac{C}{L}} = 50\sqrt{\frac{0.000159}{0.063}} \approx 2.50,$$
$$f_{\text{resonance}} = \frac{1}{2\pi\sqrt{LC}} = \frac{1}{2\pi\sqrt{0.000159 \times 0.063}} \approx 50\,\text{Hz}$$

3 Islanding Detection Techniques

The main purpose of the islanding condition detection methods is to determine whether the islanding has occurred by monitoring some electrical parameters and load demand on the grid and DG sides. Islanding detection methods can be divided into 5 categories: active, conventional passive, remote, hybrid, and improved passive (signal analysis and ML-based) methods. Figure 5 shows islanding detection methods. In the sub-headings, the methods are detailed.

3.1 Conventional (Local and Remote) Techniques

Local methods (Passive: over/under frequency and voltage (OFP/UFP, OVP/UVP), rate of change frequency (RoCoF) frequency, phase jump detection, etc. Active: sandia frequency shift, active power, reactive power, harmonic signal injection,

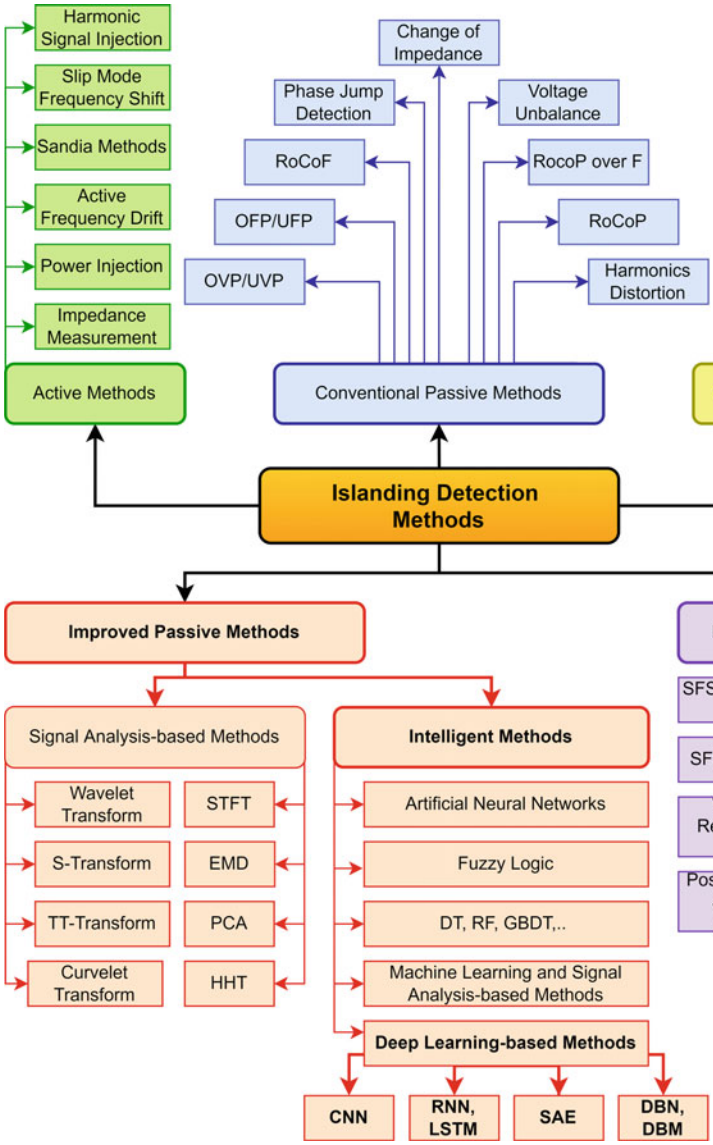

Fig. 5 Islanding detection methods

impedance measurement, etc.) have several drawbacks, including difficulty in determining a threshold value, uncertainty due to operating conditions, and susceptibility to noise. Also, they contain a large NDZ. In the active method, an additional disturbance signal is given to the system from the outside and the islanding condition is detected by monitoring the changes. Although NDZ is relatively low compared to conventional passive methods, signals injected from the outside into the system can cause PQ degradation. In addition, detection times are slower than passive methods. NDZ is low in remote methods (transfer trip, phasor measurement unit (PMU)-based scheme, programmable logic controller (PLC)-based scheme, etc.), but the cost is quite high [1, 6].

3.2 Signal Analysis-Based Methods

Signal analysis methods have a much more flexible structure as they offer the chance to observe both the time and frequency domain properties of the signals. Many signal analysis methods such as FT, short-time Fourier transform (STFT), Hilbert–Huang transform (HHT), wavelet transform (WT), s-transform (ST), TT transform, curvelet transform (CT), empirical mode decomposition (EMD), principal component analysis (PCA), etc., are used in the literature [1, 6]. There are some disadvantages to signal analysis approaches. STFT has a fixed time–frequency window resolution and cannot provide appropriate information for all event signals. WT is heavily influenced by noise. Spectral leakage influences the performance. ST is not good at real-time applications. Also, ST may cause a false estimation of harmonics. HHT applied to narrowband only. TT transform has high complexity. Furthermore, all methods have a computational burden and are not robust to noise [14].

Figure 6 provides a flowchart for the signal analysis methods. As seen, in these methods, field transform is performed to the event signal first and its coefficients/features are extracted. Threshold values are determined with empirical tests afterward, and islanding/non-islanding events are detected according to the feature parameters. Applications with threshold values show trends in false detection and missed detection due to difficulties in choosing values. This causes problems especially for signals with high noise conditions when the nominal even and the fault state are very close.

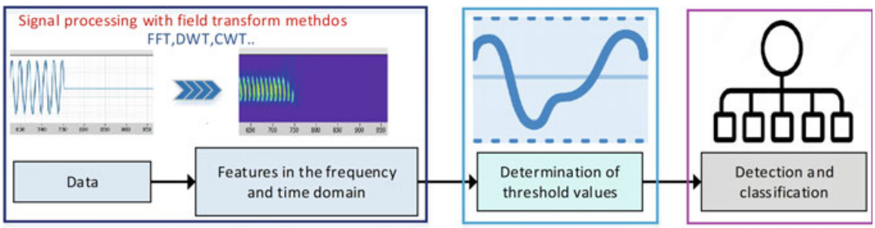

Fig. 6 Flowchart of signal processing-based method [9]

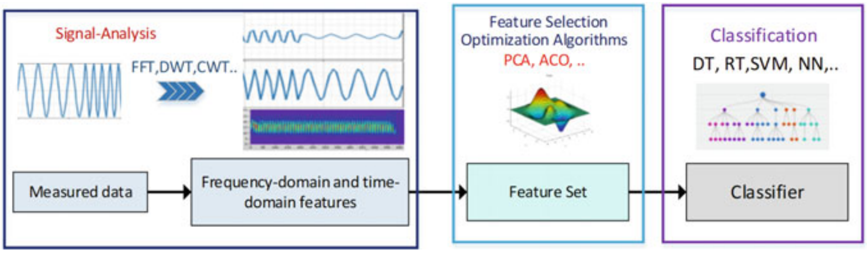

Fig. 7 Flowchart of signal analysis, feature selection, and classifier-based method [11]

3.3 Machine Learning-Based Techniques Using Signal Analysis, Feature Selection, and Classifier Methods

To overcome the limitations of traditional methods, intelligent methods using signal processing, feature selection, and classifier-based three-stage ML techniques are presented [14–17]. A flowchart of the ML approaches using signal analysis, feature selection, and classifier is shown in Fig. 7. In these methods, in the first step, the signal analysis method is applied to the event signal and feature extraction is performed using statistics. The second step is the selection of features that affect the classifier's performance. However, the feature filtering optimization process is time-consuming and tedious. Besides, it's worth noting that the original feature set is still manually selected. In the last stage, event classification is performed using the selected features. The ability of conventional three-stage ML methods to reveal attributes in raw data is limited compared to DL and requires an expert in the training process. In DL, new features emerge spontaneously by training the data, while in ML, the features must be defined correctly by the users. As a result, it is seen that while the traditional ML approach achieves very high accuracy in noise-free conditions, this accuracy decreases under high noise conditions.

3.4 Deep Learning-Based Techniques

DL techniques have automatic feature extraction capability, eliminate human involvement, it has closed-loop feedback. These methods can automatically extract features without the need for a signal processing step. Unlike traditional neural network structures, DL algorithms extract features in complex data using multiple layers. When DL is used to solve islanding identification difficulties, can streamline procedures, enhance accuracy, and reduce the need for human intervention. The differences between traditional ML methods and DL are given below:

- DL algorithms for training require more data than ML classifiers.

- While new features emerge spontaneously by training the data in DL, ML classifiers need to define the features correctly by the users.
- Deep neural networks (DNNs), which contain much more mathematical operations than classical ML give higher accuracy results in high-dimensional data thanks to these features.
- In ML, problems are divided into small parts and the results are combined into a single result. In DL, on the other hand, step-by-step problem solving is approached.

DL architectures can be examined in four different groups according to the training algorithms used. Examples of commonly used DL architectures are convolutional neural network (CNN), deep belief network (DBN), stacked auto-encoder (SAE), and long short-term memory (LSTM).

- Convolutional neural network (CNN)-based algorithms [18]: CNN, one of the widely used DL algorithms, is a DNN equipped with one or more convolutional layers followed by one or more feedforward layers. Classical CNN architectures are formed by cascading convolutional layers, pooling layers, and fully connected (FC) layer structures. Besides, dropout and batch normalization are often used to standardize inputs and prevent overfitting. The data to be used in the input layer is given to the relevant network as raw. The size of the data directly affects the accuracy of the network. As the data capacity grows, higher memory and training time are needed. The conversion process on the input data is provided with filters. With the activation function, the linear structure in the convolution layer is activated by transforming it into a nonlinear structure. The pooling layer is used after the activation function and reduces the input size for the next convolution layer. In this way, the memorization of data is prevented, and the calculation cost is reduced. The fully connected layer comes after these layers and depends on all areas of the convolutional layer before it. The dropout layer, on the other hand, can be used in these architectures in some cases to prevent the network from overfitting. Finally, classification is made in the output layer and the Softmax function is generally preferred because of its success. It produces a certain amount of output according to the classification type of the network.
- Long short-term memory (LSTM)-based algorithms: Recurrent neural networks (RNN) are one of the types of artificial neural networks, and it is formed as a result of the connection of several units consisting of directional loops with each other. The structure of the network has the potential for the entry-level neural network plan to predict the next data using the previous data. The most widely used structure in RNNs is LSTM. Consisting of memory cells and gates, LSTM is produced as a solution to the vanishing gradient problem and to overcome complex time series. LSTM architecture has three gates input, forget and output, fixed fault loop, output activation function, and peephole connections. Memory cells store information with the control of gates. There are input gates, output gates, and forget gates, which are used to control the flow of information into and out of the memory cell. LSTM is effectively used in sequential modeling tasks such as text classification and time series modeling. The application principle is

the same as the basis of artificial neural networks, and it is based on the input vector multiplied by the weight matrix and summed with the bias vector, and passed through an activation function. Models using multiple LSTM layers are called deep LSTM (DLSTM).

- Stacked autoencoder (SAE)-based algorithms: Autoencoders (AE) are neural networks that obtain a generally lower-dimensional representation of the data and use that representation to produce the same data as output. With this feature, the training of self-encoders, which is an example of notation learning, takes place through unsupervised learning. AE has a feedforward structure; this neural network may have one or more hidden layers. The main difference between AE and conventional artificial neural networks is the size of the output layer. In an AE, the size of the output layer and the size of the input layer are the same. Islanding and PQE signals have a complex relationship. Therefore, using just one AE is not enough. A single AE stands out in SAE classification problems because it cannot reduce the dimensionality of the input features. SAE consists of multiple encoders.
- Deep belief network (DBN)-based algorithms: In ML, DBN is a class of DNN that consists of multiple layers of hidden nodes, with connections between layers but not between nodes. DBNs can be viewed as a combination of simple, unsupervised networks such as restricted Boltzmann machines (RBM) or AEs. Each RBM layer is connected with both previous and subsequent layers. However, the nodes of any layer do not communicate with each other horizontally. DBNs can classify or cluster for unsupervised learning with a Softmax layer as the last layer. DBN architectures are applied to image recognition and generation.

4 Proposed Hybrid Model Using CNN and LSTM

ML-based islanding detection approaches are including three steps: signal processing, feature filtering, and classification. However, the ability of conventional three-stage ML methods to reveal attributes is limited compared to DL and requires an expert in the training process. Also, three-stage ML methods are not robust to noise. Signal processing and feature selection stages cause an extra computational burden. Human intervention at this stage makes the closed-loop control seen in DL structures impossible. To solve these problems, a novel multiple DL-based models are suggested in this study. In Fig. 8, the general structure of the DCNN, DLSTM, and proposed hybrid CNN-LSTM-based DL method is shown. In the study, it is tried to find the best of the existing deep learning algorithm outputs. Thus, choosing the best result is aimed to increase the accuracy and reliability of the system. This method provides reliably detecting islanding conditions differing from conventional methods that cause false detections due to load demands and noises in the signal. This method will be discussed in detail in this section.

The number of layers, layer order, and parameter selection in the DCNN model may differ based on the model designer. The data for CNN models is passed through

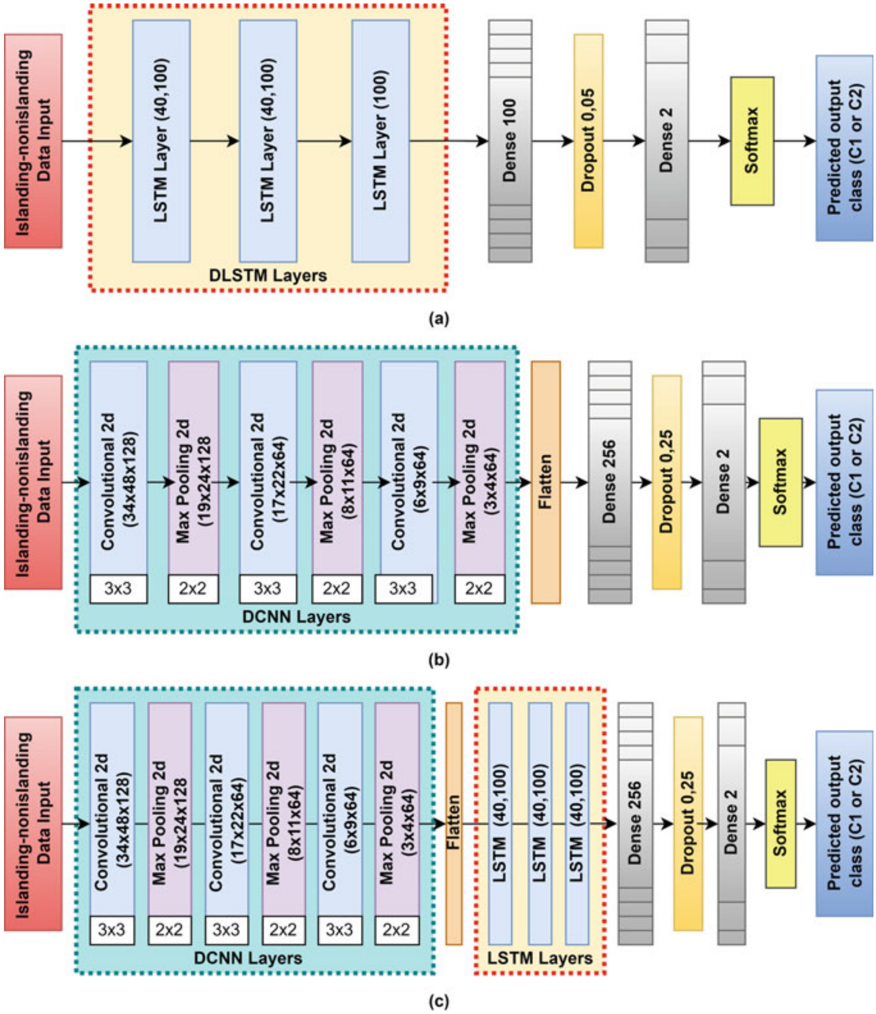

Fig. 8 **a** DLSTM algorithm, **b** DCNN algorithm, and proposed DCNN-DLSTM-based method

the network layers, and the weights are updated and transferred to the next layer. The overall error value is computed by subtracting the DCNN response from the targeted result. A backpropagation technique is used to distribute the obtained error to all weights in the network. The influence of each weight on total error is determined using stochastic descent-based optimization approaches. To get the best network performance, each iteration aims to lower the overall error. Several models are formed in this study by changing various parameters such as ordering layers in the DCNN structures, kernel dimensions, activation functions, and optimizer functions, filter dimensions. Figure 8a shows the model parameters that provide the highest accuracy for the DCNN algorithm. RELU is used as the activation function in the CNN algorithm. In the FC layer, the sigmoid activation function is used. Dropout and batch normalization are used to standardize inputs and prevent overfitting.

In Fig. 8b, model parameters are shown in the case where the most suitable model providing the highest accuracy for the DLSTM algorithm to be used for island detection is created. This model is determined for the best-performing case by modifying the hyper-parameters on the network and using optimization methods. After choosing the most suitable LSTM model, the effects on the accuracy of the model are investigated by changing parameters such as the most appropriate input parameters using this model and changing the training test rates to determine a faster islanding detection.

In this study, a hybrid network called DCNN-DLSTM combining DCNN and DLSTM algorithms is proposed for islanding/non-islanding event classification. DCNN and DLSTM models are created separately in the previous stage and combined to achieve better performance. The important information of the input samples is revealed in the first stage with CNN. The LSTM neural network, on the other hand, is designed to train and classify islanding and non-islanding conditions in the second step. The motivation to use LSTM in this model is to extract the dependencies between each feature row from the CNN network. The model parameters selected by considering the accuracy and loss factor consist of the number of convolutional layers, kernel size, maximum pooling, and the number of neurons in the fully connected layer. Model parameters are optimized by training with different options to achieve maximum performance. RELU is used as the activation function in the CNN algorithm. In the FC layer, the sigmoid activation function is used. In Fig. 8c, model parameters are shown in the case where the most suitable model provides the highest accuracy for the DCNN-DLSTM algorithm.

4.1 Results

The number of training sets reached 7000 samples for DCNN, DLSTM, and proposed hybrid models. Generated test samples for islanding and non-islanding classes are given in Table 2. Class C1 shows islanding events, while class C2 covers non-islanding events such as PQEs.

The classification test results of the proposed method have given in Table 3. Accuracy performance is very high for test data containing noise at different signal-to-noise ratio (SNR) values and covering all scenarios. The proposed approach classifies islanding conditions caused by CB opening and minor disturbances caused by switching and operating conditions in a microgrid.

The performance comparison of DLSTM and DCNN and the proposed DCNN-DLSTM-based hybrid method at different noise levels is given in Table 4. The hybrid model provides better performance than DCNN and DLSTM in accuracy and noise immunity. LSTM is to extract the dependencies between each row of features. With

Table 2 Generated test samples for islanding and non-islanding classes

Class	Events	Number of test samples
C1	Islanding in different power mismatches (at the PCC of the hydrogen energy-based DG)	300
C2	Voltage sag (switching on loads and switching off capacitor banks)	100
	Voltage swell (switching offloads and switching on capacitor banks)	100
	Induction motor starting	100
	Presence of drive systems	100
	PV disconnection	100
	Line-to-ground (LG), two line-to-ground (LLG), and three line-to-ground (LLLG) faults	200

Table 3 The classification test results of the proposed method

Class	Number of test samples	Corrections	Accuracy rate (%)
C1	300	295	98.33
C2	700	688	98.29

Table 4 Comparison

	Accuracy rate (%)		
Model	No-noise	Low-level noise (SNR: 40 dB)	High-level noise (SNR: 30 dB)
DCNN	98.43	97.13	96.46
DLSTM	98.25	97.56	96.79
Proposed hybrid model	98.85	98.13	98.01

this advantage, the proposed model shows performance superiority in automatic feature extraction.

The detection time is within the IEEE standards for the hybrid DCNN-DLSTM with a binary classifier. NDZ region is almost zero for the proposed method, and its comparison with UVP/OVP, and UFP/OFP methods is shown in Fig. 9.

5 Discussion and Conclusion

Previous ML-based islanding detection approaches are including three steps: signal processing, feature filtering, and classification. In the signal analysis step, all methods are affected by noise. The feature filtering and feature optimization process are

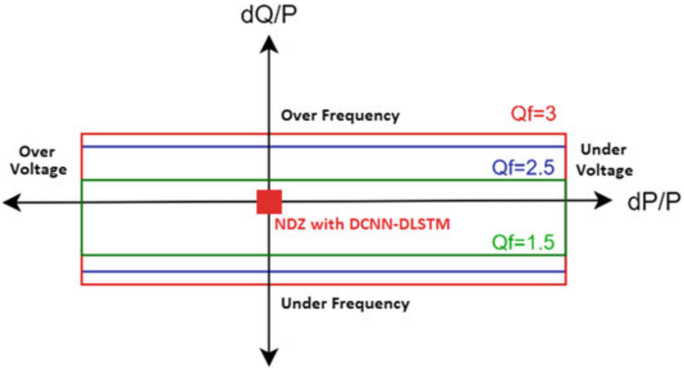

Fig. 9 NDZ region comparison with UVP/OVP and UFP/OFP method for different Q_f

tedious and time-consuming. Besides, signal processing and feature selection cause a computational burden. To solve these problems, a novel multiple DL-based models are suggested. A DL-based islanding classification method using LSTM and CNN is proposed for the classification of islanding and non-islanding PQEs such as sags, swells, and frequency deviations in DG-based microgrid considering the DG load demand. The important information of the input samples is revealed in the first step with CNN in the proposed method. The LSTM is designed to train and classify events in the second step.

A DCNN-DLSTM-based method is analyzed under different scenarios that will occur depending on the situation on the demand side. The accuracy results are also compared with the DCNN and DLSTM models. The proposed method has 98.85% accuracy under no-noise and 98.01% high-level noise conditions. The detection time is within the IEEE standards and NDZ is almost zero for DCNN-DLSTM with a binary classifier.

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Comparison of PV Power Production Estimation Methods Under Non-homogeneous Temperature Distribution for CPVT Systems

Cihan Demircan, Maria Vicidomini, Francesco Calise, Hilmi Cenk Bayrakçı, and Ali Keçebaş

Abstract The way to increase energy generation in a standard photovoltaic (PV) or photovoltaic/thermal (PV/T) system is the tracking of the sun and/or concentrating to increase the solar energy coming into the field. As the radiation is increased in both concentrated PV and PV/T systems, both PV power output and PV module temperature increase. The fact that the PV module temperature increases and exceeds the reasonable level reduces the life of solar cells and permanently damages the cells. The way to prevent this is to cool the PV modules. In other words, thermal energy is absorbed by integrating the thermal system. Thus, both electrical and thermal energy needs will be met easily, and a concentrating photovoltaic thermal (CPVT) system produces both electricity and thermal energy from the sun. Electrical and thermal behavior analyzes of CPVT systems are important issues in order to robust and accurate deciding for electrical and thermal power production. In a previous study, finite volume methods were applied for thermal analysis of the CPVT system. Temperature distribution of the PV modules and CPVT surfaces was done. In the numerical analysis; power/temperature coefficient-based method was used for electrical power estimation. In this chapter, power/temperature coefficient-based and five parameter models of PV modules were presented and discussed for forecasting of electrical power production. Decided to PV module temperature in power/temperature coefficient model and temperature distribution applications on diode model were discussed.

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Power/temperature-based power estimation methods are depending on first, medium, and end PV module temperature. However, different case studies for CPVT electrical power production forecasting methods were investigated.

Keywords Solar energy · Photovoltaics · Concentrating photovoltaic thermal · Electrical modeling · Uncertainties

1 Introduction

The current traditional energy use causes global climate changes with increase in energy demand in recent years. Therefore, the creation of an energy structure that does not or is less risky for the environment gains importance in terms of sustainable development and climate changes [1]. The limited energy and the increasing demand for energy every day encourages the use of more efficient energy from energy sources. Renewable energy sources (RES) are environmentally friendly, non-renewable and intermittent types of energy. The ever-increasing energy demand and the inability to store energy encourage more efficient use of energy produced from RES. Recently, due to the decrease in initial investment costs, the electricity produced from the sun as RES has increased by society and industry, institutions and organizations [2].

Solar photovoltaic (PV) cell includes semiconductor materials and converts the electricity from the sun. The quantity of solar radiation on the PV surface is raised in the concentrating PV (CPV) cells. However, PV module temperature increases because of the rising of solar radiation in CPV cells. Therefore, over temperatures can be permanently damaged to solar cells. PV cells are actively or passively cooled in order to prevent the damaging. In order not to damage the PV cells, they are actively or passively cooled. A channel through which a fluid flows is used on the PV back surface for active cooling. Thus, solar energy is converted into heat energy together with electricity. Systems operated in this way are referred to as concentrated PVT (CPVT).

The solar radiation for the parabolic-trough node has uniform value for CPVT systems. And the PV modules are, respectively, cooled by the fluid as the fluid flows through the parabolic trough. On the other hand, as the liquid flows to the end of the parabolic trough, the cell temperatures rise and the liquid temperature rises. PV module temperature is higher than previous node. For this reason, inhomogeneous temperature distribution occurs in PV modules. For this reason, the current and voltage values of PV modules vary. The realization of these mismatches creates power losses in the PV. In this chapter, uncertainty of the amount of electricity from the CPVT system was evaluated. Uncertainty analysis in output power estimation caused by nonlinear behavior of solar cells and environmental factors in literature studies was presented below. In addition, literature studies about CPVT systems were mentioned.

The performance of PV systems varies according to material properties, operating conditions, and environmental conditions (temperature, solar radiation, wind speed, etc.). Mallick and Eames [3] evaluated the electrical performance analysis of the low-concentrated PV system. Current–voltage (I–V) and power-voltage (P–V) curves were used for electrical performance analysis. According to the findings, weak optical coating between the unit concentrator and the PV module causes more than one MPP. Maka and O'Donovan [4] performed dynamic performance analysis with thermal and electrical models for a triple junction solar cell-based CPV module. It has been observed that the annual change in cell temperature above 80 °C covers 13% in the summer season. In addition, it has been emphasized that one of the causes of current mismatching in the triple junction solar cells is spectral variation. Durusoy et al. [5] determined the correction factor as 0.33 for the calculation of solar radiation incident on the back surface of the bifacial PV module. The annual PV efficiency calculation error was 1.4% after the correlation methods. Metlek et al. [6] estimated the effect of temperature on electrical power in the natural zeolite PVT system using a long short-term memory algorithm. It has been seen that the proposed algorithm accomplished the accurate predictions with very small errors. Navabi et al. [7] presented work for accurate estimation of output energy using PV module equivalent circuit models. The proposed modeling in the study for the planning studies of PV systems was compared with the system supervisor model and RETScreen software. According to the monthly analyzes, the average error of the developed model was below 5%, while the other techniques were found to be above 10%. Carullo and Vallan [8] analyzed the long-term performance of PV power plants. According to the power plant data and their calculations, the most uncertainty is seen in the average PV efficiency with 1.3%, while the plant with CIGS thin film PV module is more efficient than the others. Makrides et al. [9] presented a study on the errors and uncertainties in estimating the annual energy yield of different types of PV modules. They have been reported that the accuracy is increased by the correlation of the temperature coefficient in the single-point efficiency model. In addition, study has been observed that the results of the single diode model better match the real data. Dubard et al. [10] investigated the uncertainties in PV performance measurement traceability. According to obtained results; uncertainty varies between 2.5 and 10% in the PV production line. And practically it is between 3% and 5%, while it is as low as 2% for the crystalline silicon reference modules. They emphasized that the uncertainty developed is a key factor for the PV market and has a significant impact on the economy and the environment. Dirnberger et al. [11] presented a study on the performance ratios and uncertainties of eight different PV module types. In the analysis with STC power uncertainty, it was observed that the uncertainties changed between 1.8 and 3.0%. Roberts et al. [12] presented system models and analyses of the process from global solar radiation to alternating current output for PV performance evaluation. In another study [13], literature reviews on the correct estimation of the maximum power point for quality assurance of large-scale PV plants were evaluated and compared with experimental data. In the study evaluation for four different PV technologies, it was stated that CdTe and CIGS thin film technologies are similar to the technologies with crystalline silicon. In terms of amorphous/microcrystalline PV technologies, it is declared that the seasonal variation is 3.5% of the STC power. It has been emphasized that the uncertainties about the models for such a situation are great. Zhang et al. [14] performed the analysis of parameter uncertainty on the reliability and performance of PV cells with the quasi-Monte Carlo method. In the study based on the single diode model, small series internal resistance and large parallel internal resistance were reported for increasing the amount of power generation. Bharadwaj and John [15] proposed a sub-cell model for PV modules with hotspots. In the proposed model, the shading cross-section and PV equivalent circuit parameters are correlated. According to the tests performed in the shading conditions, the proposed model has proven to be useful with an output prediction accuracy of 93%. Chin and Salam [16] developed the three-point approach technique for PV parameter extraction. According to the obtained results, the standard deviation of the proposed method is lower, and it is superior to other methods in parameter extraction. Li et al. [17] has been reported that I-V characteristic curve-based methods are used more frequently in PV parameter extraction and maximum power point estimation. In this chapter, power/temperature coefficient-based and five-parameter models of PV modules were presented and discussed for forecasting of electrical power production. Decided to PV module temperature in power/temperature coefficient model and temperature distribution applications on diode model were discussed. Power/temperature-based power estimation methods are depending on first, medium, and end PV module temperature. In the literature studies about CPVT systems were presented as follows.

Ben Youssef et al. [18] developed a two-dimensional numerical model for electrical and thermal performance analysis in a triple-junction CPVT system. Thermal model and electrical performance evaluations based on current–voltage curves in a CPVT system with north–south solar tracking in the steady state and transient analysis carried out by Wang et al. [19]. According to the comparison with experimental studies, it has been seen that the thermal model in the transient analysis gives more realistic results. Bernardo et al. [20] implemented and simulated a parabolic-trough CPVT system with a triangle receiver. Calise and Vanoli [21] zero-dimensional energy balance equations, finite volume methods [22], high-temperature solar trigeneration system [23], air holding unit with dryer [24], CPVT assisted heating and cooling [25], thermodynamic performance evaluation [26], thermal modeling and parametric analysis [27], optical modeling and optimization [28], CPVT-based air heating and thermal energy storage [29], effect of different absorbers on performance [30], absorption-thermoelectric cooling [31], optical design [32], and electro-thermal analysis [33]. Various studies have been carried out on the CPVT and PVT systems. Demircan et al. [2] investigated electrical connections of PV strings in CPVT systems. Afzali Gorouh et al. [34] designed a low-concentrated CPVT system with an A-shaped PV array. The system was evaluated with zero-dimensional thermal modeling, optical analysis using Monte Carlo light tracking software, and experimental studies.

In this chapter, power/temperature coefficient-based and five-parameter model of PV module were presented and discussed for forecasting of electrical power production. Decided to PV module temperature in power/temperature coefficient model and temperature distribution applications on diode model were discussed. Power/temperature-based power estimation methods are depending on first, medium, and end PV module temperature. However, different case studies for CPVT electrical power production estimation methods were investigated.

2 System, Modeling, and Evaluation

In this section, the two string-triangular-based CPVT system is described. The finite volume method for the analysis of the temperature distribution of the triangular receiver CPVT system is briefly summarized. Furthermore, mathematical modeling for PV modules in CPVT systems is introduced. Information on the comparison of power generation forecasts is presented.

2.1 Definition of the CPVT System

The schematic diagram of the parabolic-trough CPVT system is shown in Fig. 1. As seen in the figure, this system consists of a concentrator concentrated on the trough, a triangular parabolic trough, a fluid channel within the trough, and PV modules positioned on the triangular trough. Mirror is used to reflect the sunlight coming through the concentrator into the triangular trough. The triangular prismatic trough is placed at the focus of the concentrator. While one surface of the trough looks perpendicular to the sunlight, the junctions of the other two surfaces form the concentrator two reflection zones. Sunlight from these regions is reflected to the PV modules on the trough. No PV module is added to the trough surface perpendicular to the sun when the purpose of thermal treatment is desired. In response to the electricity production in the PV modules, there is an increase in both the PV module and triangular trough temperatures. A fluid channel is placed in the triangular trough to reduce the temperature here.

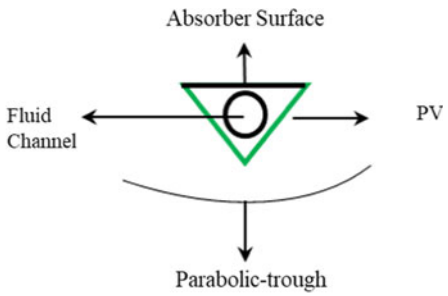

Fig. 1 Parabolic-trough-based CPVT system diagram

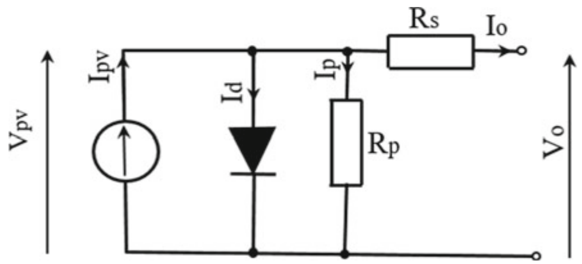

Fig. 2 PV equivalent circuit for five parameters

2.2 *Mathematical Modeling of PV*

Mathematical modeling is necessary to discuss the dynamic behavior of PV modules under certain conditions. Single diode model, double diode model, triple diode, or multiple diode models have been proposed to model the nonlinear dynamic behavior of solar PV modules. The most frequently used and preferred model among the models is the single diode model (SDM). This model is based on four and five parameters. It takes into account series and parallel resistance values. When the SDM is compared with two-diode model, it is most simple. The equivalent circuit of the PV module based on five parameters is given in Fig. 2.

In this section, the single diode model consisting of five parameters in the PV modules of the CPV system is discussed. For four and five parameter-based mathematical models of such a PV module, the relationship between current and voltage can be given in Eqs. (1) and (2) [35].

$$I_o = I_{pv} - I_d\left(e^{\frac{q(V_O + R_S I_O)}{nkT}} - 1\right) \tag{1}$$

$$I_o = I_{\mathrm{pv}} - I_d\left(e^{\frac{q(V_O + R_S I_O)}{nkT}} - 1\right) - \frac{V_o + R_s I_o}{R_p} \tag{2}$$

where I_o, I_{pv}, and I_d denote the currents in load, PV and diode, respectively. In addition, q, k and n are, respectively, the electron charge, the Boltzmann constant and the diode ideality factor. R_s and R_p represent the series and parallel resistances, respectively.

Under short-circuit current and open-circuit operating conditions, the current–voltage relations can be written as follows [35]:

$$I_{sc} = I_o - I_d\left[e^{\frac{q I_{sc} R_s}{nkT}} - 1\right] - \frac{I_{sc} R_s}{R_p} \tag{3}$$

$$0 = I_o - I_d\left[e^{\frac{q_s V_{oc}}{nkT}} - 1\right] - \frac{V_{oc}}{R_p} \tag{4}$$

Table 1 The datasheet values of the TPS105S-5W PV module [37]

Parameter	Value	Parameter	Value
I_{sc} (A)	0.32	V_{oc} (V)	21.5
I_{mp} (A)	0.29	V_{mp} (V)	17.5
λ (%/K)	0.05	β (%/K)	-0.32
Sizes (cm)	19.3 × 23.3	Weight (kg)	0.54

where I_{sc} and V_{oc} denote the short-circuit current and open-circuit voltage, respectively. The estimated I_{sc} and V_{oc} values according to the PV module temperature are as follows, respectively:

$$I_{sc,T} = I_{sc}\left(1 + \lambda\left(T_{pv} - 25\right)\right) \tag{5}$$

$$V_{oc,T} = V_{oc}\left(1 + \beta\left(T_{pv} - 25\right)\right) \tag{6}$$

where λ, β, and T_{pv} denote the current–temperature coefficient, the voltage-temperature coefficient, and the PV module temperature, respectively.

In the CPVT system, TPS105S-5W PV module are taken into account. The parameters for the PV modules used are given in Table 1 [2, 33, 37]. Their mathematical modeling is performed in the MATLAB/SIMULINK program [36] using five-parameter equivalent circuit of PV modules.

One of the important factors affecting energy performance in photovoltaic energy conversion systems is environmental parameters. The main affecting environmental parameters are solar radiation, ambient temperature, and wind speed. The efficiency of PV modules under certain environmental conditions is expressed as follows:

$$\eta_{PV} = \eta_{ref}\left(1 - \gamma\left(T_{pv} - 25\right)\right) \tag{7}$$

where η_{ref} is the reference efficiency value and is calculated according to the power value under standard test conditions (1000 W/m^2, 25 °C). γ is the power/temperature coefficient of the PV module. This coefficient is taken as 0.45% for crystalline PV modules and 0.25% for amorphous PV modules [38]. T_{PV} shows the PV module temperature. The power that the PV module can produce at a given concentration ratio (C), solar radiation (G), and T_{PV} module temperature, as

$$P_{PV} = CGA\eta_{PV} \tag{8}$$

In this chapter, temperature coefficient-based power production per PV module in CPVT system and total power production of CPVT system in FVM method are compared with five-parameters single diode model (SDM) based PV power production estimation. In order to SDM power estimation, temperature distribution is applied on PV mathematical modeling of the PV strings. However, electrical power uncertainty of the CPVT system is evaluated.

In the FVM, the size of the CPVT system is divided into each node. When the next fluid outlet temperature is calculated, this temperature is considered the next node's inlet temperature and outlet temperature of that node. In the next node, the energy balance equations are analyzed again by taking advantage of the temperatures obtained from the previous nodes. Thus, the numerical analysis of the CPVT system is evaluated with the help of the solutions obtained for each point. The five energy balance equations of the CPVT system are taken into account, respectively for upper surface—PVT, fluid channel—metallic surface, PVT—metallic surface, upper surface of the triangular receiver—substrate and parabolic-trough concentrator.

The finite volume method is based on obtaining the energy balance equations between the triangular receiver and the parabolic-trough concentrator [21, 22, 33]. And the least squares method was used to solve the energy balance equations. In the finite volume method, the length of the CPVT system is divided into nodes. When the next fluid outlet temperature is found, this temperature value is accepted as the outlet temperature of that node and the inlet temperature of the next node. At the next node, the energy balance equations are solved again by utilizing the temperature values obtained from the previous nodes. Numerical modeling is done using MATLAB program [36] and COOLPROP [39] for thermo-physical specifications of refrigerant fluid and air. Thus, thermal analysis of the CPVT system is performed. Among the environmental conditions in the operating conditions of the CPVT system, the ambient temperature is 25 °C, the wind speed is 2 m/s, the direct radiation is 800 W/m^2 and the total radiation is 1000 W/m^2. The concentration ratio of the system is about 2.61. The results obtained are given and discussed below. In this chapter, R134a fluid is considered for effects of non-homogeneous temperature distribution on electrical power production. Obtained results are presented and discussed the next section. However, electrical power production uncertainties are evaluated in this study.

3 Results and Discussion

In the CPVT system, two string PV modules are used for electricity production. In order to utilize of thermal energy in PV modules fluid channel and refrigerant fluid is used. However, electrical and thermal energy of incoming solar energy is useful. Parabolic concentrator is reflected to incoming solar radiation to PV cells for increasing of solar radiation. Thus, electricity and thermal energy increased.

Datasheet values for a PV module (TPS105S-5W) used in PV arrays on trough in the CPVT system are listed in Table 1. The mathematical modeling results based on the diode model obtained under standard test conditions (STC) (1000 W/m^2, 25 °C) and different radiation conditions are shown in Fig. 3. As seen in Fig. 3, the output power (5.07 W) reaches its maximum value when the module voltage is at 17.5 V for 1 kW/m^2. Beyond this point, the output power starts to decrease.

The I–V and P–V curves in the PV module for different module temperatures at 1000 W/m^2 are plotted in Fig. 4. In the context of Fig. 4, it is observed that the output power drops rapidly as the open circuit voltage is approached due to the non-linear

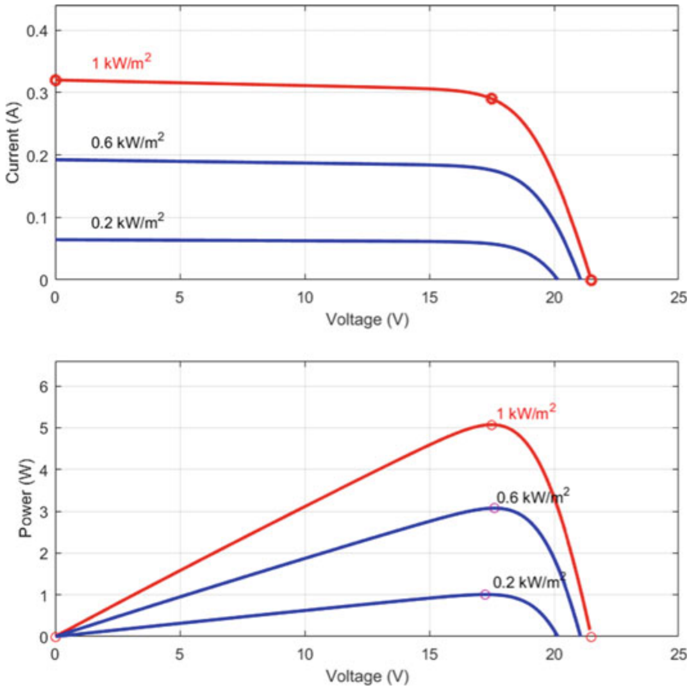

Fig. 3 Voltage, current, and power curves of PV module for various solar radiation

behavior. An increase in module temperature will slightly increase the I_{sc} value, while a greater decrease in the V_{oc} voltage. PV power generation also reduces [2].

In this chapter, temperature coefficient-based power production per PV module in CPVT system and total power production of CPVT system in FVM method are compared with five parameters SDM-based PV power production estimation. In order to SDM power estimation, temperature distribution is applied on PV mathematical modeling of the PV strings. However, electrical power uncertainty of the CPVT system is evaluated. Obtained results are presented as follows.

In the thermal analysis results of the CPVT system using FVM method for different fluid inlet temperatures are given in Fig. 5. As can be seen in this figure, PV temperature (T_{cpvt}) increases when the fluid temperature increases for each node. However, non-homogeneous temperature distribution is available in CPVT system characteristics.

Power production for the PV module at each node is given in Fig. 6. Power production decreases at each node due to fluid temperature. Power production per module for 50 °C fluid inlet temperature is 8.35 W in the first node. It decreases up to 6.52 W at the end of the CPVT system. On the other hand, T_{cpvt} exceeds 110 °C when the fluid inlet temperature increases. However, power production decreases according to low inlet temperature.

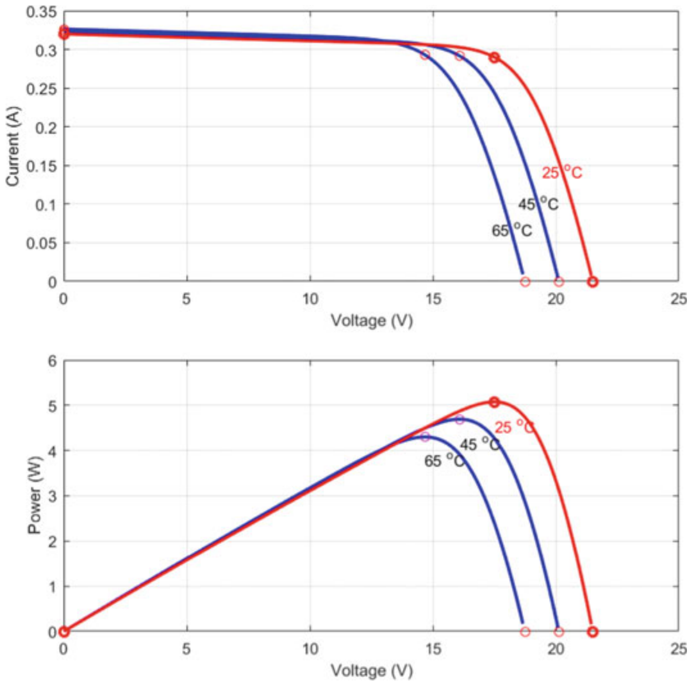

Fig. 4 Voltage, current, and power curves of PV module for different module temperature

The goal of this chapter is power uncertainty of the CPVT system. The reason for the non-homogeneous temperature distribution is given below due to fluid circulation in the fluid channel of the triangular receiver in the parabolic-trough CPVT system. Single diode model application results for non-homogeneous temperature distribution and numerical method results of the system are given following. However, power uncertainty is evaluated for the CPVT system under non-homogeneous temperature distribution.

In the finite volume methods, temperature coefficient-based efficiency and power estimation method are used in given Eq. (8). Power estimation results for FVM and SDM methods are presented in Table 2 for different fluid inlet temperature (T_{in}). Moreover, current–voltage and power-voltage variations under non-homogenous temperature gradients are presented in Fig. 7. As can be seen the results of two different methods, power estimation results are close to each other in terms of maximum power point of PV modules. When the T_{in} is 30 °C of the CPVT system, power differences is approximately 14 W. And, it decreases 4.4 W for the other T_{in} parameters. On the other hand, operating voltages in maximum power point decrease by increasing of fluid temperature. As a result, high fluid inlet temperatures decrease the power production and can cause to damage of PV cells. Therefore, low inlet temperature for R134a fluid should be preferred for more electricity production and

Fig. 5 Temperature distribution of CPVT system

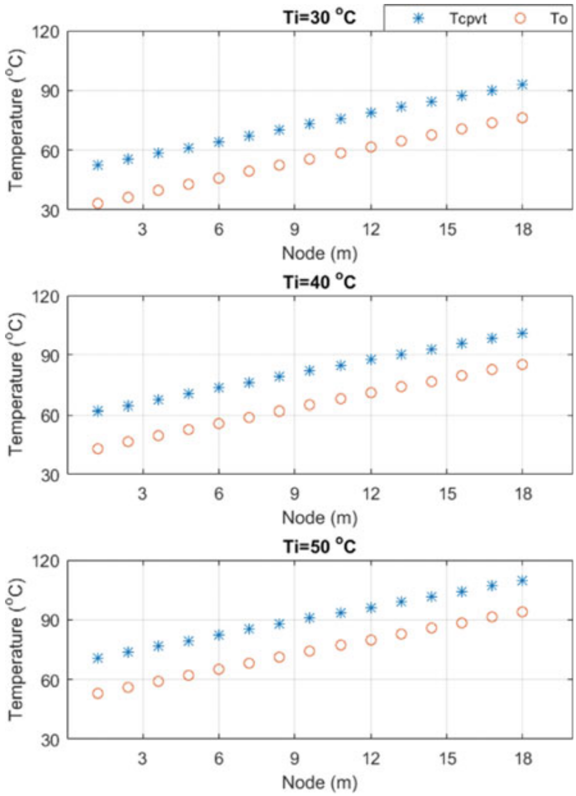

Fig. 6 Electric power production per module at each node in CPVT system

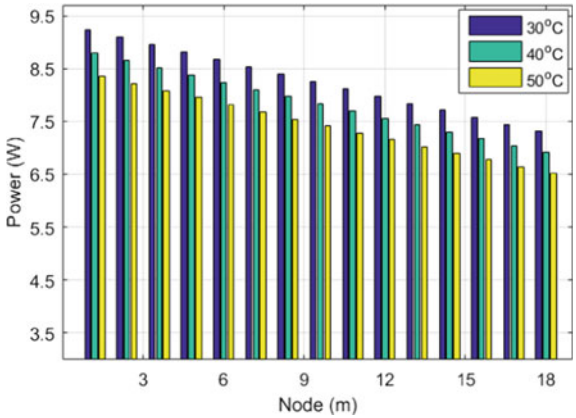

Table 2 Estimated total electricity production of the system for FVM and SDM methods

P_{el}/T_{in}	30 °C	40 °C	50 °C
$P_{el,FVM}$ (W)	1486.72	1411.47	1336.24
$P_{el,SDM}$ (W)	1470.71	1405.89	1340.75

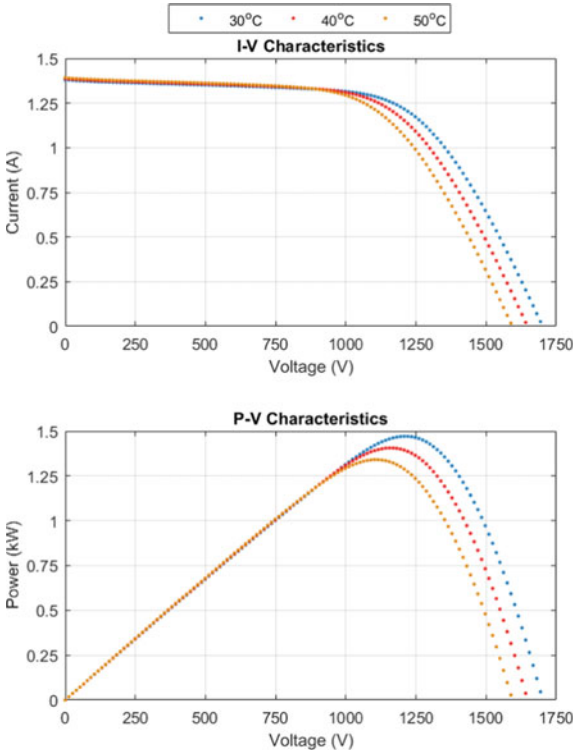

Fig. 7 I voltage, current and power characteristics of CPVT system under non-homogeneous temperature distribution

physical protection of PV cells. In this way, solar energy could be efficiently used for a long lifetime.

As a result, obtained results for two estimation methods are in good agreement with each other. Power differences are very less. And power uncertainty of the CPVT system could be negligible according to two different methods when the PV module operates at maximum power point. However, two different methods are reliable for performance analysis of the CPVT system.

4 Conclusions

In this chapter, temperature coefficient-based power estimation method and maximum power point in single diode modeling of the CPVT strings are compared for power uncertainty analysis. Maximum power difference was obtained for 30 °C fluid inlet temperature as well as 14 W. It is smaller than 5 W for other fluid temperature when the maximum power point tracking is used in CPVT system. As a result, power uncertainty of the CPVT system could be negligible according to FVM and SDM methods. On the other hand, when the fluid inlet temperature increases, PV module temperatures reach up to 110 °C. This temperature should be carefully chosen and designed for R134a refrigerants. In addition, operating at maximum power point of the CPVT string is useful for efficient solar energy utilization.

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Renewable Energy Predictions: Worldwide Research Trends and Future Perspective

Esther Salmerón-Manzano, Alfredo Alcayde, and Francisco Manzano-Agugliaro

Abstract The objective of this chapter is to have a global perspective of the research related to renewable energy predictions and thus determine the worldwide research trends in this field. For this purpose, all the publications indexed in the Scopus database with these terms in the title, abstract or keywords were studied, obtaining more than 10,000 records. The subject categories were analyzed, and the most important ones were engineering and energy. Regarding the trend in the number of publications, two periods have been detected, from 1996 to 2007 and from 2008 to the present with a growing interest. Regarding countries, it has been observed that this ranking is led by the United States, followed by China, and in third place by the United Kingdom. The main institutions with more than 100 publications were: North China Electric Power University (China), National Renewable Energy Laboratory (USA), Ministry of Education (China), Technical University of Denmark (Denmark), and Tsinghua University (China). The study of key words made it possible to detect the main clusters that have been considered significant and are the ones that set the research trends in this field. Three clearly differentiated clusters have been found. The first one focused on the search for alternative renewable energies, in its beginnings mainly with the use of biomass. The second one is more focused on electric power transmission network, and the third one is focused on wind energy and its forecasting, where modern computational and mathematical techniques are being used.

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Keywords Renewable energy resources · Renewable energies · Renewable energy · Forecasting · Wind power · Renewable energy source · Solar energy · Electric power transmission networks

1 Introduction

From the beginning of the mankind, its development has been characterized by the use of alternative forms of energy according to its needs and availability [32]. Energy resources were always based on renewable energies in the form of biomass, wind, water, or sun. They were used as a source of fuel, or as mechanical energy for the beginnings of industry such as hydraulic or wind mills [33].

In this sense, any process that does not alter the thermal balance of the planet, that does not generate irrecoverable waste, and that its rate of consumption does not exceed the rate of recovery of the energy source and the raw material used in it is renewable [4].

Nowadays, the main resources of renewable energy are: solar energy, wind energy, hydropower, biomass, biogas, ocean energy, or geothermal energy. The search for a balance between supply and demand is a particularly relevant fact as it is not feasible to conserve energy [23]. In addition, in the energy sector, this information becomes even more important due to the degree of uncertainty involved in predicting highly volatile factors, such as natural or meteorological phenomena, as well as other variables that have a major impact on markets, such as legislative or socioeconomic changes [2, 3].

There is an ever-increasing increase in electricity demand and an increasing need to use renewable resources to supply this demand [24]. Renewable energy sources imply complexity when planning and managing energy demand, given the high volatility in their generation through non-storable resources such as wind or solar radiation.

Thus, nowadays, to know the availability of the renewable resource is essential to maintain a given energy level at the lowest possible cost [18]. Thus, generation forecasting for renewable energy sources allows energy managers to have a maximum performance tool that helps them to optimally manage their renewable resources [22]. This further enables energy pricing [60]. Therefore, the prediction of demand or the behavior of the electricity price to make the best decision to sell or buy energy is currently a need for any company in the sector, whether it is a producer, distributor, marketer, or system operator.

In this chapter to identify the current directions of research and trends in the field of renewable energy prediction, a bibliometric study of publications indexed in the Scopus scientific database will be conducted, which has proven useful for similar studies [39].

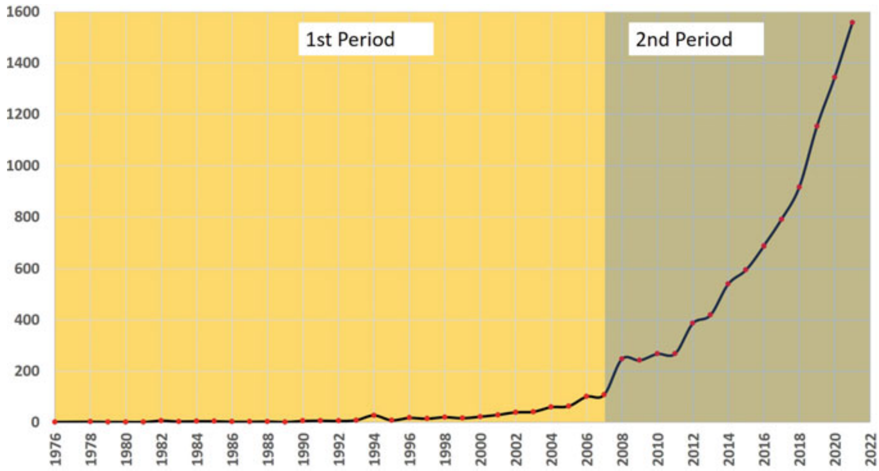

Fig. 1 Periods of the worldwide scientific production in renewable energy predictions

2 Data

The data in this chapter were extracted from the Scopus database, the exact search query was: TITLE-ABS-KEY ("Renewable Energ*") AND (TITLE-ABS-KEY (prediction*) OR TITLE-ABS-KEY (forecast*)).

For this search, more than 10,000 results were obtained from 1976 to 2021, the last year considered because of the completeness of the data. Of these scientific documents, 58% were articles in scientific journals (of which 4% were review papers), 39% were conference papers, and only 3% were books or book chapters. The low percentage in books and book chapters indicates that it is a scientific topic still rising and with scientific progress [55, 56]. The newest technologies start in the scientific meetings, and when they reach a certain maturity, they are published in articles in journals and later in specialized books.

Figure 1 shows the evolution of these publications, where two periods have been distinguished. The first one from 1976 to 2007, in which 100 publications per year were published. The second period starts in 2008 with almost 250 publications, growing exponentially until the last year studied, 2021, with more than 1500 publications in that year.

3 Subjects from Worldwide Publications

One of the most important aspects in a bibliometric analysis of this nature is to check the distribution of publications by scientific category, to determine where the publications fall [57]. In this sense, Fig. 2, research is led by the engineering

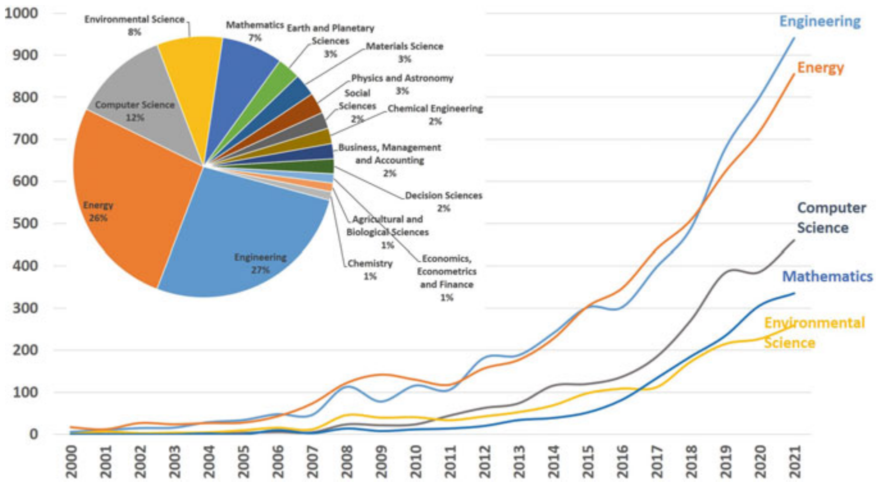

Fig. 2 Distribution and evolution of Scopus categories on renewable energy predictions

category with 27% of the total, followed closely by the energy category (26%). Between these two main categories, they account for more than 50% of the total scientific production of renewable energy prediction. The most cited publication in the engineering category is related to wind energy volatility [62], while for the energy category it is a review paper on wind speed and power generation forecasting [28].

The computer sciences category is very relevant with 12%, showing the prominence of computational techniques in this scientific field, which are supported by the field of mathematics (in fifth position with 7% of the total). The most cited work for computer science is a research on short-term residential load forecasting based on LSTM recurrent neural network [26]. The most cited paper for mathematics is a review paper of neural networks applied for wind speed prediction [58].

The fourth scientific field is environmental sciences with 8%. This was to be expected with renewable energies not only because of the resource itself but also because of the effort to achieve climate neutrality such as the decarbonization of the electricity sector, and for this one is the link between environmental conservation and the large-scale deployment of wind and photovoltaic energy. The most cited work in this scientific field deals with the production of bioethanol from rice straw [7].

In addition, Fig. 2 shows the evolution of scientific production in each of these five main categories. In this sense, it can be observed how the energy category has dominated until the year 2019, where the engineering category has surpassed it and is maintaining its position as leader in research in renewable energy prediction. The computer science category has been in third place since 2011, where it clearly maintains this position. The mathematics category has held the fourth position since 2017, the year in which environmental sciences moved to the fifth position.

4 Countries, Affiliations, and Their Main Topics

Another important factor to consider when studying the state of the art in this field is the geographical distribution. Therefore, Fig. 3 shows all the countries in the world that have publications on renewable energy prediction, as the legend of the figure itself suggests, the more intense the color, the greater the number of publications. In this sense, research is led by China, followed by the USA. The most cited work from China is the aforementioned review on wind speed and power generation forecasting [28], and from the USA is the aforementioned review on wind power volatility [62]. At a greater distance is India in third place, followed by the UK and Germany, in fifth and sixth place, respectively. The most cited paper from India is the one on bioethanol production from rice straw [7]. The most cited paper from the UK is an engineering paper related to the estimation of spinning reserve requirements in systems with a significant penetration of wind generation [43], and the one from Germany is on life cycle dynamics assessment of renewable energy technologies [44]. To complete this group of countries with more than 300 publications in order, there are: Italy, Spain, Australia, Japan, France, and South Korea: Italy, Spain, Australia, Japan France, and South Korea.

On the other hand, if we analyze the publications of the main affiliations with the highest scientific production, we obtain Table 1. In the Fig. 4, the affiliations with at least 50 publications have been listed. Twenty-six affiliations have been found, of which thirteen are from China. Followed by Portugal with three affiliations, Denmark with two, and USA, Italy, Bangladesh, Switzerland, France, Singapore, Australia, and Japan with one.

Looking at the main keywords of these institutions, Table 1, there are no major differences in the fields of specialization. The top five affiliations (North China Electric Power University, National Renewable Energy Laboratory, Ministry of Education China, Technical University of Denmark, and Tsinghua University) have wind power

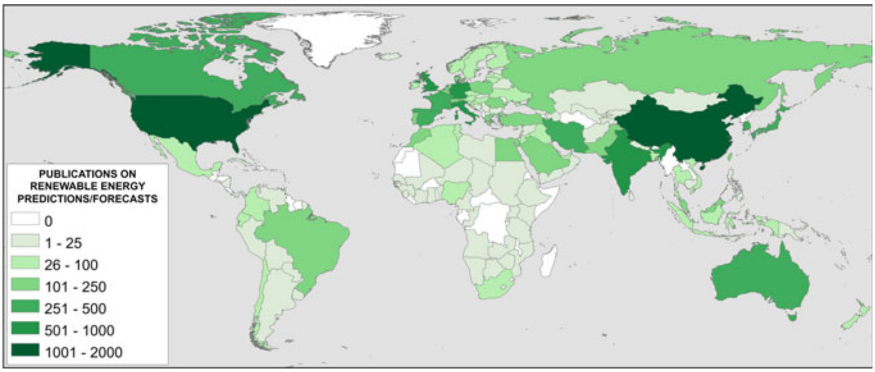

Fig. 3 Worldwide geographical distribution of the scientific production on renewable energy predictions

Table 1 Main affiliations and their main keywords

Affiliation	Country	*N*	Keywords			
			1	2	3	4
North China Electric Power University	China	160	Renewable energy resources	Wind power	Renewable energies	Forecasting
National Renewable Energy Laboratory	US	148	Renewable energy resources	Wind power	National renewable energy laboratory	Forecasting
Ministry of Education China	China	144	Forecasting	Wind power	Renewable energy resources	Electric power transmission networks
Technical University of Denmark	Denmark	124	Wind power	Renewable energy resources	Forecasting	Renewable energies
Tsinghua University	China	124	Renewable energy resources	Forecasting	Renewable energies	Wind power
Politecnico di Milano	Italy	84	Renewable energy resources	Renewable energy source	Forecasting	Neural networks
Shanghai Jiao Tong University	China	76	Renewable energy resources	Renewable energies	Electric power transmission networks	Forecasting
Chinese Academy of Sciences	China	75	Forecasting	Renewable energies	China	Wind power
State Grid Corporation of China	China	68	Renewable energies	Renewable energy resources	Electric power transmission networks	Forecasting
Aalborg University	Denmark	67	Renewable energy resources	Renewable energy source	Energy management	Forecasting
Zhejiang University	China	66	Renewable energy resources	Forecasting	Renewable energies	Renewable energy source
China Electric Power Research Institute	China	66	Electric power transmission networks	Wind power	Renewable energies	Renewable energy resources

(continued)

Table 1 (continued)

Affiliation	Country	*N*	Keywords			
			1	2	3	4
Universidade do Porto	Portugal	65	Forecasting	Renewable energy resources	Wind power	Renewable energies
Southeast University	Bangladesh	62	Forecasting	Renewable energy resources	Wind power	National renewable energy laboratory
Institute for Systems and Computer Engineering, Technology and Science	Portugal	62	Renewable energy resources	Forecasting	Wind power	Renewable energies
ETH Zürich	Switzerland	61	Renewable energy resources	Renewable energy source	Wind power	Forecasting
Tianjin University	China	60	Forecasting	Renewable energy resources	Wind power	Renewable energies
CNRS Centre National de la Recherche Scientifique	France	57	Renewable energy resources	Renewable energies	Forecasting	Optimization
North China Electric Power University Baoding	China	56	Wind power	Forecasting	Renewable energies	Renewable energy resources
Shandong University	China	55	Renewable energies	Renewable energy resources	Forecasting	Wind power
Universidade de Lisboa	Portugal	53	Renewable energy resources	Forecasting	Renewable energies	Wind power
National University of Singapore	Singapore	51	Renewable energy resources	Forecasting	Renewable energies	Smart power grids

(continued)

Table 1 (continued)

Affiliation	Country	*N*	Keywords			
			1	2	3	4
UNSW Sydney	Australia	51	Renewable energy resources	Forecasting	Electric power transmission networks	Renewable energies
Xi'an Jiaotong University	China	50	Wind power	Renewable energy resources	Renewable energies	Forecasting
The University of Tokyo	Japan	50	Renewable energy resources	Forecasting	Renewable energies	Renewable energy
Huazhong University of Science and Technology	China	50	Renewable energy resources	Wind power	Forecasting	Renewable energies

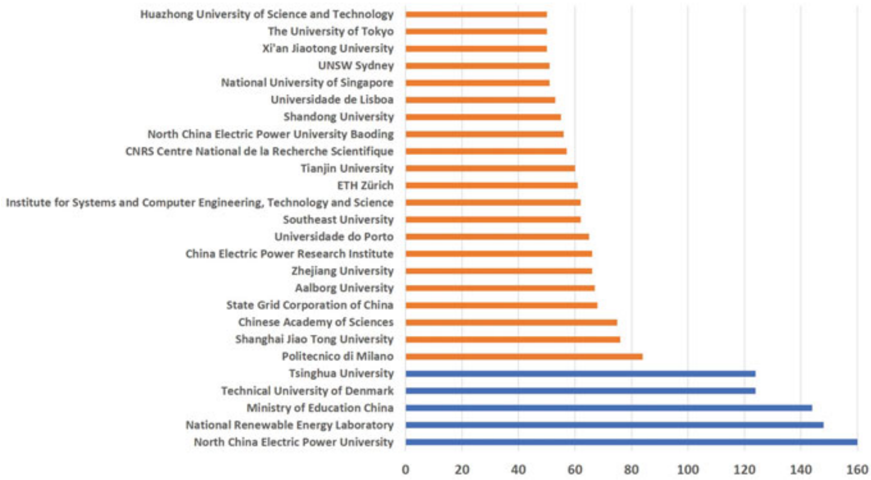

Fig. 4 Main affiliations on renewable energy predictions (more than 50 publications)

among their main keywords. The keyword Electric Power Transmission Networks also appears in the top institutions such as Ministry of Education China, Shanghai Jiao Tong University, or State Grid Corporation of China. The keyword Neural Networks appears only in Politecnico di Milano, although it is one of the top 20 keywords as will be seen below.

In summary, it can be said that all these institutions have similar objectives as their main keywords coincide in almost all of them and can be summarized in these five: renewable energy resources, renewable energies, wind power, forecasting, and electric power transmission networks.

5 Keywords from Worldwide Publications

Keywords make it possible to classify the entries in the indexing and information retrieval systems in the databases of a particular manuscript or subject area [54]. Keywords then become an essential two-way tool, i.e., for those who write and for those who search for information on related manuscripts or subject areas. In general, the number of keywords in most scientific journals ranges between 3 and 10. Consequently, their importance should not be undervalued or underestimated when considering them, since it could become difficult to disseminate a manuscript and even fail to detect its relationship with other similar ones, due to the inadequate use of keywords.

Therefore, from all these publications, to try to narrow down the topics on which they focus, it is necessary to analyze the keywords that these research papers deal with. As can be seen in Table 2, apart from the obvious search terms (renewable energy resources, forecasting, or renewable energies), the fourth place is held by wind power, which is the renewable energy that occupies most scientific effort in trying to determine its periodicity and, therefore, its forecasting as an energy resource. It is striking that electric power transmission networks are above solar energy. This may be due to the importance of the renewable energy resource on the design of energy transmission networks or that solar energy in this sense is well studied, i.e., energy-efficient solar hours in a specific area of the planet. To compare the relative importance of these keywords, they have been represented by a cloud of words, Fig. 5.

6 Worldwide Research Trends: Cluster Analysis

The analysis of the relationships between keywords makes it possible to obtain the scientific communities or clusters in which these publications are grouped [55, 56]. For the analysis of this section, the software Vosviewer (https://www.vosviewer.com/) available online has been used, which has proven to be useful for this analysis in many scientific fields.

Figure 6 shows the representation of the three clusters retrieved with the total number of publications analyzed. Table 3 shows the main keywords of these clusters, and in the last column a name has been proposed for their identification.

The first cluster can be considered as starting in 2001 with the objective of optimizing the overall performance of isolated and weakly interconnected systems in liberalized market environments, increasing the share of wind and other renewable forms of energy [14]. This cluster has a high component of studies of the potential of bioenergy already since 2002 and for studies of its temporality in very different fields [59], biogas [13], horticultural waste [9] for electricity production [1], grassland [53], woody [48], and vegetable residues such as those of tropical fruits like avocado [45], mango [47], date [12], or loquat [49]. More recently, the production of hydrogen from plant residues such as those from the wine industry has been introduced [40].

Another major line of study of this cluster is the energy market and its implications on greenhouse gas emissions [21], both in high-energy consuming countries such as the United Arab Emirates [24], US [63], or China [35], and in medium energy consuming countries such as Spain [36] or Italy [10].

The second cluster, focused on renewable energy resources, started in 1991 with the study of geothermal power in Iceland [27], and is closely related to optimization techniques both in terms of the use of different methods [6] and the optimization of small installations [5]. In this cluster, energy storage plays an important role, and therefore there are researches related to the improvement of batteries [20], especially those based on lithium [61] and their incorporation into microgrids based on renewable energies [30, 41]. Within this cluster, the electric power transmission network is of great relevance. For this purpose, forecasting models for photovoltaic energy [51] and wind energy [28] are under study. Solar energy prediction studies range from direct irradiance data of high quality [31], the possible shading of large installations

Table 2 Top 20 keywords related to renewable energy predictions

Keyword	*N*
Renewable energy resources	3.703
Forecasting	3.076
Renewable energies	2.579
Wind power	2.148
Renewable energy	1.858
Renewable energy source	1.678
Electric power transmission networks	1.304
Solar energy	1.215
Weather forecasting	982
Optimization	931
Neural networks	791
Energy policy	730
Solar power generation	729
Photovoltaic cells	717
Energy management	713
Alternative energy	709
Wind	692
Smart power grids	690
Renewable resource	685
Energy utilization	673
Energy efficiency	627
Costs	616
Electric utilities	616
Scheduling	609
Energy storage	578
Stochastic systems	573
Electric power generation	571
Prediction	548
Machine learning	534
Solar radiation	524
Commerce	508

for a specific latitude [11, 42], or for isolated rooftop installations [2, 46] to cloudiness prediction models [34]. And, the other major source of energy that influences the power grid is wind energy, and therefore its forecasting is fundamental [28] both for the possible available energy and for the selection of the type of turbine for a wind farm [38]. Some authors also point out the possible power quality disturbances due to the incorporation of renewable energy into the energy system [37].

Fig. 5 Cloud of keywords from the scientific production of the renewable energy predictions

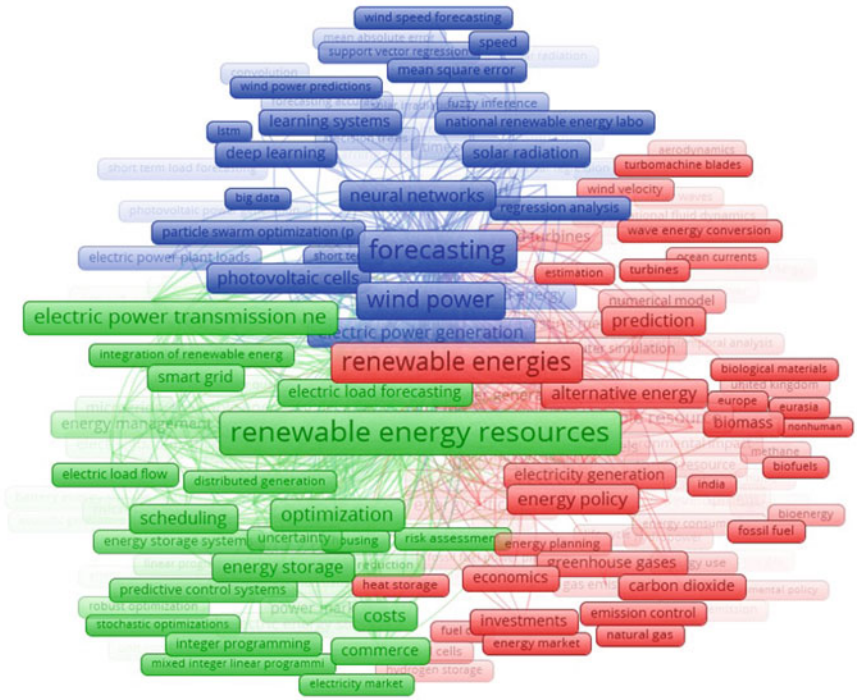

Fig. 6 Relationship between renewable energy predictions

Table 3 Main clusters (Fig. 6), weight, and names

Color	Weight (%)	Main keywords	Cluster name
Red	40	Renewable energies, alternative energy, energy policy, prediction, greenhouse gases, carbon dioxide, biomass, biofuels, biological materials, energy efficiency, energy utilization, electricity generation, turbines, energy market	Renewable energies
Green	34	Renewable energy resources, electric power transmission network, electrical load flow, distributed generation, optimization, energy storage, electricity market, smart grid, risk assessment, uncertainty, predictive control systems	Renewable energy resources/electric power transmission network
Blue	26	Forecasting, wind power, electric power generation, solar radiation, photovoltaic cells, bid data, deep learning, regression analysis, learning systems	Wind power/forecasting

The third cluster is mainly focused on wind energy and its possible estimation. Once estimates of the availability of this resource have been made at the local [16], regional [19], or country level [15], it is necessary to identify the periodicity of the resource [17], based on complete data series that sometimes need to be revised or completed with modern mathematical techniques such as wavelet [64]. Short-term forecasting employs from simple statistical methods [8] to very diverse algorithms such as security-constrained unit commitment (SCUC) algorithm [62], or f-ARIMA models for day-ahead wind speed forecasting [25]. More recently, neural networks are used for short-term wind power and load forecasting [50], where the use of particle swarm optimization (PSO) stands out [52].

7 Evolution of the Research and Future Perspective

The evolution of research trends has also been analyzed through their key words. Figure 7 shows the evolution of the keywords of all the analyzed publications. Table 4 shows the main keywords for each period. At the beginning of the period studied is in the year 2012, where differences begin to emerge. In that year, publications related to biofuels and biomass are reflected. A little later, in 2014, the impact on the electricity market also begins to be studied.

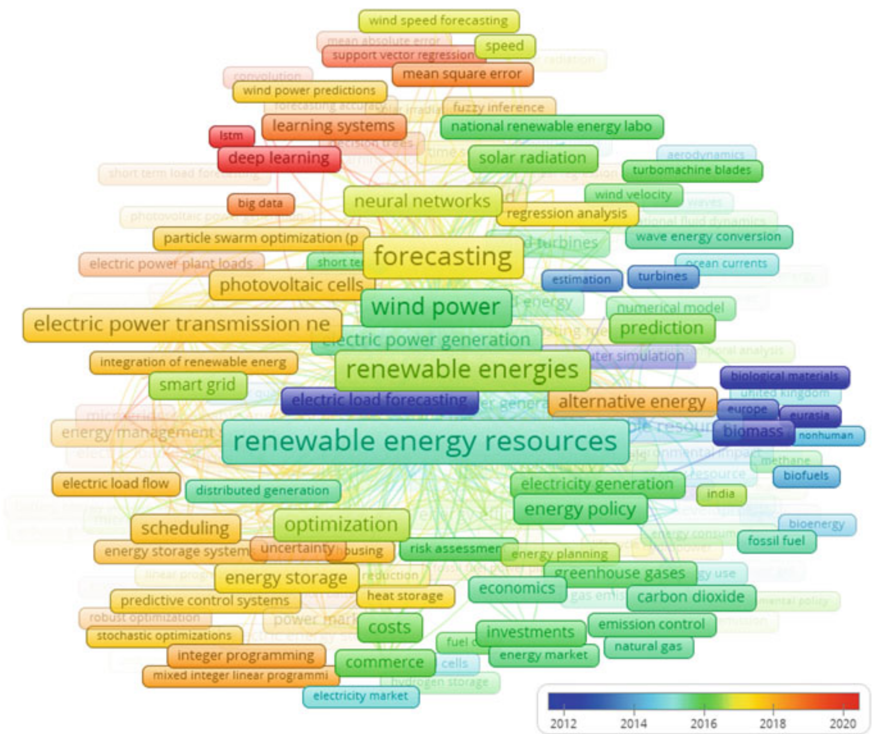

Fig. 7 Trend of renewable energy predictions

Table 4 Main clusters (Fig. 7)

Color	Years	Main keywords	Cluster name
Blue	2012–2014	Biomass, biological materials, electric load forecasting, biofuels, electricity market, ocean current	Bioenergy
Cian–green	2015–2016	Energy policy, costs, investments, emission control, wind power	Energy policy
Yellow	2017	neural network, forecasting, electric power transmission network, energy storage	Transmission network
Orange–red	2018–2020	Bid data, learning systems, deep learning, lstm	Computer sciences

In the following years, studies on the economic viability of the sector (costs vs. investments) and energy policy were included. As renewable energy sources, a boost is given to wind power and, on the other hand, the advantages for the environment, such as the reduction of emissions, begin to be highlighted. In 2017, studies on the electricity grid itself as a whole (electric power transmission network, energy storage) highlighted, and its study with neural network, or how forecasting can affect the network. In parallel, forms of energy storage are being studied.

The last period analyzed in Table 4, from 2018 to 2020, appear with great strength the computer techniques applied to the study of energy such as Bid data, learning systems, deep learning, LSTM (Long Short Term Memory). The latter, LSTM, is an algorithm of neural networks but differs from the standard ones in that it has feedback connections [26]. Deep Learning techniques are booming especially for PV power prediction models [29].

The global demand for renewable energy will increase significantly in the very near future given the global energy and geopolitical situation to avoid dependence on other countries. The two renewable energies with the greatest projection are wind and solar, being the forecasting of the production of the first one where the greatest efforts will continue to be made from the scientific and technological point of view.

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Models of Load Forecasting

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Abstract World is growing every day in many aspects. Economic growth, population growth, technical growth, etc., leads to a common factor: a never-ending increasing demand of energy. To meet this energy demand, fossil fuels will burn out soon and renewable energy is a long way to go to certain advancements to meet the energy demand. Here, load forecasting (LF) will play a key role to predict the future load so that the energy can be generated in efficient way which will be less harmful to environment and more economical. LF is done using various models such as long short-term memory (LSTM), artificial neural network (ANN), and support vector machine (SVM), which predicts the future load based on historic data. In this chapter, we have discussed about LF, types of LF, factors affecting LF, and a comparative review has been performed of recently developed techniques and models with benchmarks models used for LF.

Keywords Load forecasting · Load forecasting models · Machine learning · Deep learning · Artificial intelligence

Abbreviations

ANN	Artificial Neural Network
ANFIS	Adaptive Network-Based Fuzzy Inference System
ARIMA	Autoregressive Integrated Moving Average
ARMSE	Average Root Mean Squared Error
BDLSTM	Bayesian Deep Long Short-Term Memory
BPNN	Backpropagation Neural Network
CCRN	Correlation Based Convolution Recurrent Network
CNN	Convolutional Neural Network
DRNN	Deep Recurrent Neural Network

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DNN	Deep Neural Network
DT	Decision Tree
ELM	Extreme Learning Machine
ES	Expert Systems
ETS	Exponential Smoothing
GA	Genetic Algorithm
GBRT	Gradient boosted Regression Trees
KNN	K-Nearest Neighbor
LR	Linear Regression
LSTM	Long Short-Term Memory
LTLF	Long-Term Load Forecasting
MAE	Mean Absolute Error
MLP	Multilayer Perceptron
MLR	Multiple Linear Regression
MAPE	Mean Absolute Percentage Error
MTLF	Medium-Term Load Forecasting
NN	Neural Network
OP-ELM	Optimally Pruned Extreme Learning Machine
PDRNN	Pooling-based Deep Recurrent Neural Network
PLCNet	Parallel Long Short-Term Memory-Convolutional Neural Network
QLSTM	Pinball Loss Guided Long Short-Term Memory
RF	Random Forest
RFR	Random Forest Regression
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
SDTRM	Spark Decision Tree Regression Model
SGBT	Spark Gradient-Boosted Trees
SRFRM	Spark Random Forest Regression Model
STLF	Short-Term Load Forecasting
SVM	Support Vector Machine
SVR	Support Vector Regression
SVRL	Support Vector Machine with Linear Kernel
SVRP	Support Vector Machine with Polynomial Kernel
SVRR	Support Vector Machine with Radial Kernel
WNN	Wavelet Neural Network
XGB	Extreme Gradient Boosting

1 Introduction

Most of the industries depend on electrical energy therefore its availability is of economic importance throughout the world. A continuous, affordable, and reliable source of electricity is of great importance to achieve all the objectives mentioned we apply ‘Electrical Load Forecasting’ on a power grid [1].

‘Electrical Load Forecasting’ is a computational method by means of which we predict the future load demand with the help of past and present data of load demand. It acts as an important factor during power system planning, operation, and control [2].

By performing ‘Electrical Load Forecasting’ for the residential and commercial load’s the electricity generation and distribution companies can schedule functionally ahead and develop energy conservation among the users [3].

The objectives of ‘Electrical Load Forecasting’ are power system:

- Planning
- Operation
- Finance
- Development
- Maintenance.

The load prediction can be calculated for about 2–4 h for operative purposes or as much as about 30 years for planning purposes [2].

2 Types of Load Forecasting

Electrical Load Forecasting’ can be majorly categorized into three types:

(1) Short-Term Load Forecasting (STLF)
(2) Medium-Term Load Forecasting (MTLF)
(3) Long-Term Load Forecasting (LTLF) [4].

- In STLF, the load is being predicted from few hours to week ahead to curtail the running and transmitting cost. The methods commonly used for forecasting are the LSTM, neural network (NN), random forest regression (RFR) method, and SVM method [5]. It is used in load flow study and further to take decisions for the prevention of overloading. Its applications are allocation of spinning reserve, unit commitment calculation, maintaining proper fuel stock, maximizing utility revenue, development of small generation schemes, etc.
- In MTLF, the load is being predicted in a range of few weeks to 10 years ahead so that the systematic planning can be maintained [6]. The multilayer perceptron (MLP) and SVM are some of the methods used for the forecasting. Its application include deciding rate structures of different consumers, calculating capital cost of different generation options, annual planning and budget allocation for fuel requirements, and other operational purposes etc.
- In LTLF, the load is being predicted in a range of a decade to 50 years ahead so that development planning can be eased upon. Neural network (NN), genetic algorithm (GA), fuzzy rules, SVM, wavelet neural networks, and

expert systems. Its applications are national grid expansion, demand side management, selection of substation capacity, development of a new power plant, 'Fuel Mix' decision, etc. [7].

3 Factors Affecting Load Forecasting

3.1 Meteorological Factors: It is Further Divided into Two Sub Parts that are 'Climate' and 'Weather'

- Climate is the mean weather over a finite period in an area. With a change in climate influences the load consumption consequently. It is a major factor in long-term load forecasting.
- Weather is an atmospheric condition that mostly exists for a temporary period of time in an area. It is reasonable and important to take weather factor into consideration for STLF. It affects the load demand for domestic and agricultural customers. The alterations in weather alters the utilization of appliances in accordance with comfort level of consumers. It is a major factor to be considered in short-term forecasting.
- 'Weather' further incorporates four parts, i.e., temperature, cloud cover, wind speed, and humidity.

3.2 Temporal and Calendar Factors

- The impact of the calendar difference of the same month between different years are known as the calendar factors.
- Load consumption varies between different seasons due to dissimilar beginning and ending timings of day and night, hours of difference between timings of day or nights; increased residential load at weekends compared to weekdays, timings of the year leading to festivals or big events.

3.3 Economy Factors

- The economic factors play significant role in load forecasting, such as type of customers, per capita income, demographic conditions, gross domestic product (GDP) growth, industrial development, and cost of electricity. The daily load curve of developing and developed countries is distinct as maximum loading occurs at different time period, for developing countries, it is at evening time between 06:00 pm and 09:00 pm, whereas for developed countries the peak load timings are from 11:00 am to 04:00 pm [8].

- Spot market prices and short-term futures contracts are a crucial factor for STLF, whereas the LTLF are not very much affected by these factors.
- Some countries use these factors to reduce load during peak load hours be keeping a difference in electricity prices between peak and off-peak load hours consumed by residential households. If the price of electricity is increased, then domestic consumption will reduce because the price of electric power and the consumer's financial condition varies the load consumption [9].

3.4 Random Factors

- Huge industrial loads in a power system sometimes cause sudden imbalance in load consumption; these sudden imbalances are known as random factors.
- Special events such as festival or regional happenings are also considered as important factors for load forecasting.
- Other than these, certain situations such as the shutdown of an industry, or a big event such as sports competition, wedding season, and lockdown are the random factors affecting the load forecasting.

3.5 Customer Factors

- The various consumers such as residential and commercial so the load curve may be varying from consumer to consumer. The consumer factors of electricity consumption are the specifications or ratings of the electrical equipment of the customer. Also, the electrical equipment varies from consumer to consumer.

3.6 Factors Based on Time Horizon

- Short-Term Influence Factors: These factors frequently appear in a specific forecasting span and nearly do not have the characteristic of that time span.
- Medium-Term Influence Factors: These factors frequently last for some forecasting span and have specific characteristics of that time span.
- Long-Term Influence Factors: These factors are experienced for many forecasting periods and have especially the characteristic of that time span [8].

3.7 Other Factors

- According to the geographical areas the load curve could be different, i.e., the load curve of less populated areas will be different from highly populated.

- These factors can have more or less effect on the machine learning (ML) model, it can also have a destructive effect on a model. As the load varies the effect of various factors changes accordingly.

4 Comparative Review of Popular Load Forecasting Techniques

4.1 Techniques Based on Machine Learning

4.1.1 In Table 8 [10–14], Different Individual Models Are Compared Which Were Enhanced with the Help of Multi-processing, and it is Noticed that SVR Had the Most Significant Performance and also RF Had Lowest RMSE

See Table 1.

4.1.2 In Table 3 [15, 16], a Novel Technique Based on ML Based on Distributed Trees with Apache Spark is Applied to Some Models and Compared Using a Standard Error ARMSE Distributed Tree-Based Machine Learning with Apache Spark

See Table 2.

4.1.3 In Table 3 [17–21], the Performance of a Hybrid Model Which Combines Two Individual Models; LSTM and CNN are Compared to Various Models, and It Is Noticed That This New Model is Very Accurate

See Table 3.

4.1.4 In Table 4 [22–26], A Novel Algorithm to Select Least Cost Electric Load Forecasting Model is Used and Compared Using Correlated Meteorological Parameters

See Table 4.

Table 1 Utilization of multi-processing to improve overall performance of forecasting models

Model	Data used	Types of load forecasting	Errors (%)	Significance/remarks	Application/applicable to
Decision tree (DT)	Real-time energy consumption dataset collected at distribution transformers	STLF	RMSE = 5.67 MAPE = 10.91	Improvement in short-term forecasting accuracy and speed	Distribution transformers
Linear regression (LR)		STLF	RMSE = 5.91 MAPE = 10.0	Benchmarks performance	Non-real time forecasting
Neural network (NN)		STLF	RMSE = 14.78 MAPE = 553.29	–	Peak load reduction
Support vector regression (SVR)		STLF	RMSE = 4.87 MAPE = 5.42	Can predict the price and load more accurately	Economic load dispatch
Gradient boosted regression trees (GBRT)		STLF	RMSE = 4.26 MAPE = 11.99	–	Decisions related to increment/decrement loads
Random forest (RF)		STLF	RMSE = 4.02 MAPE = 10.64	–	Its hybrids can be used for MTLF

Table 2 Distributed tree-based ML with Apache Spark

Model	Data used	Types of load forecasting	Errors (kWh)	Significance/remarks	Application/applicable to
Spark decision tree regression model (SDTRM)	Distribution transformers real-world dataset from Spain	STLF	ARMSE = 10.8071	Two times faster execution time with the use of thread pool and fair scheduler	Distribution transformers
Spark random forest regression model (SRFRM)		STLF	ARMSE = 10.6005	High accuracy but requires more training time	–
Spark gradient-boosted trees (SGBT)		STLF	ARMSE = 11.8855	–	–

Table 3 Hybrid model which combine LSTM and CNN

Model	Data used	Types of load forecasting	Errors (%)	Significance/remarks	Application/applicable to
Parallel LSTM-CNN (PLCNet)	Real-world hourly load consumption dataset	STLF, MTLF	RMSE = 0.031 MAPE = 2.08	PLCNet out performs every other machine learning demonstrated models	Large to small loads
Autoregressive integrated moving average (ARIMA)		STLF	RMSE = 0.102 MAPE = 3.56	ARIMA—ANN hybrid models show incredible performance for linear and non-linear problems	Most suitable for very-short and short-term forecasting
Exponential smoothing (ETS)		STLF	RMSE = 0.36 MAPE = 8.81	–	–
LR		STLF	RMSE = 0.092 MAPE = 2.335	Benchmarks performance models	Very short- and short-term forecasting
SVR		STLF	RMSE = 0.272 MAPE = 7.63		–
Deep neural network (DNN)		STLF	RMSE = 0.128 MAPE = 3.62	–	–
LSTM		STLF	RMSE = 0.097 MAPE = 3.11	Performs better than most benchmarks models	Reduced artificial debugging for STLF
LSTM-CNN		STLF, MTLF	RMSE = 0.053 MAPE = 2.43	High accuracy for short term and medium-term load forecasting	Maintenance scheduling

Table 4 Novel algorithm to select least cost electric load forecasting model using correlated meteorological parameters

Model	Data used	Types of load forecasting	Errors	Significance/remarks	Application/applicable to
Deep neural network (MLR)	Time series data of hourly electricity consumption	STLF	MAPE (%) = 9.23 RMSE (kWh) = 4677.23	Economically better model for electric load forecasting	Can be used where cost is major constraint
K-nearest neighbor (KNN)		STLF	MAPE (%) = 6.07 RMSE (kWh) = 2948.49	Accuracy can be increased with increase training time	–
Support vector machine with linear Kernel (SVRL)		STLF	MAPE(%) = 10.26 RMSE (kWh) = 5120.05	Linear kernel model is less complex compared to other kernels	–
Support vector machine with linear Kernel (SVRR)		STLF, MTLF	MAPE(%) = 5.62 RMSE (kWh) = 2746.58	Radial kernel is more accurate compared to other kernels	Unit commitment transaction and other power system operations
Support vector machine with linear Kernel (SVRP)		STLF	MAPE(%) = 8.39 RMSE (kWh) = 3791.53	Polynomial kernel exhibits higher efficiency for non-linear complications	Can be used for time series prediction
RF		STLFB	MAPE (%) = 5.71 RMSE (kWh) = 2870.55	Gives more accurate results with selective features	–
AdaBoost		STLF	MAPE (%) = 8.43 RMSE (kWh) = 3913.34	–	Electricity market clearing

Table 5 Bayesian deep learning technique

Model	Data used	Types of load forecasting	Errors (%)	Significance/remarks	Application/applicable to
QLSTM	Smart meter data from the Australian grid grid	STLF	MAPE = 0.1155 MAE = 17.7268 RMSE = 21.9014		Residential and commercial loads forecasting
Bayesian deep long short-term memory (BDLSTM)		STLF	MAPE = 0.0892 MAE = 13.8607 RMSE = 17.1698	High speed and reduction in error	

4.2 Techniques Based on Deep Learning (DL)

4.2.1 In Table 5 [27, 28], the Bayesian Deep Learning technique is Used to Improve the Performance of LSTM, and the Results Are Compared with Pinball Loss Guides LSTM (QLSTM)

See Table 5.

4.2.2 In Table 6 [29–32], Clustering is Used to Enhance CNN and then Compared with Other Similar Models

See Table 6.

4.2.3 In Table 7 [33, 34], a Hybrid Model of Deep Recurrent Neural Network (DRNN) Based on Pooling is Compared with Similar Models. Based Deep Recurrent Neural Network

See Table 7.

4.2.4 In Table 8 [35], Four Hybrid Models Based on Clustering and Deep Learning Are Compared Using a Real-Life Dataset Collected from Commission of Energy Regulation

See Table 8.

Table 6 CNN based on clustering

Model	Data used	Types of load forecasting	Errors (%)	Significance/remarks	Application/applicable to
Pyramid—CNN	Power load data from SGSC project	STLF	MAPE = 39	(1) Efficient approach of grouping similar-profile energy customers (2) Elimination of need for developing and training models for individual household	Similar-profile energy customers based on clustering
Extreme learning machine (ELM)		STLF	MAPE = 122	Very poor accuracy	–
KNN		STLF	MAPE = 71	–	(1) Effective for very-short, short- and medium-term forecasting (2) Local approach instead of global approach can improve the accuracy
Backpropagation neural network (BPNN)		STLF	MAPE = 49	Large amount of training data is required for training of model	
ANN		STLF	MAPE = 47	By tuning of parameters, performance can be improved significantly	
LSTM		STLF	MAPE = 44	–	–

Table 7 Pooling-based deep recurrent neural network

Model	Data used	Types of load forecasting	Errors (kWh)	Significance/remarks	Application/applicable to
Pooling based deep recurrent neural network (PDRNN)	Smart metered data from Ireland	STLF	RMSE = 0.4505 NRMSE = 0. 0912 MAE = 0.2510	Improved efficiency and reduced error	Commercial load forecasting
ARIMA		STLF	RMSE = 0.5593 NRMSE = 0.11 MAE = 0.2998	Non suitable for nonlinear problems	Very effective for low model orders
RNN		STLF	RMSE = 0.5280 NRMSE = 0.1076 MAE = 0.2913	Large training data is required	–
SVR		STLF	RMSE = 0.5180 NRMSE = 0.1048 MAE = 0.2855	Efficiency depends on tuning of parameters	–
Deep recurrent neural network (DRNN)		STLF, MTLF	RMSE = 0.4815 NRMSE = 0.0974 MAE = 0.2698	Better performance with entropy-based training	Can be used for smart cities forecasting

Table 8 Combination of clustering and NN

Model	Data used	Types of load forecasting	Errors (%)	Significance/remarks	Application/applicable to
K-shape clustering + (DNN)	Real-life dataset from Commission of Energy Regulation	STLF	MAPE = 2.15	Very high accuracy achieved clustering methods are used in combination with DNN	Residential loads and small to medium enterprises
K-means clustering + DNN		STLF	MAPE = 2.55		
K-shape clustering + (NN)		STLF	MAPE = 2.98		
K-means clustering + NN		STLF	MAPE = 3.33		

Table 9 Combination of deep learning and k-means clustering

Model	Data used	Types of load forecasting	Errors (%)	Significance/remarks	Application/applicable to
K-means clustering + LSTM	Real-life Irish residential load dataset	STLF	MAE = 0.3791 RMSE = 0.6022	Improved prediction accuracy	Residential load forecasting
PDRNN		STLF	MAE = 0.3959 RMSE = 0.6202	Comparatively better performance then benchmarks models	–

4.2.5 In Table 9 [36], a Hybrid Model Combination of Deep Learning and k-means clustering is Compared with Another Hybrid Model, PDRNN, Based on Standard Errors MAE and RMSE

See Table 9.

4.2.6 In Table 10 [37–40], a Hybrid DNN Model Based on Two Different Techniques Transfer Learning and Meta learning is Compared to Various Models Based on Their Performance in a Residential Dataset

See Table 10.

Table 10 DNN model based on transfer learning and meta learning

Model	Data used	Types of load forecasting	Errors	Significance/remarks	Application/applicable to
Extreme gradient boosting (XGB)	Residential dataset	STLF	RMSE (kWh) = 0.261 SMAPE (%) = 32.04	Significant performance of meta learning for limited data availability	Medium–small loads
MLP		STLF, MLP	RMSE (kWh) = 0.261 SMAPE (%) = 32.23	MLP and its hybrid models can be used for MTLF	Regulatory actions
LSTM		STLF	RMSE (kWh) = 0.295 SMAPE (%) = 38.26	–	–
Sequence to sequence		STLF	RMSE (kWh) = 0.309 SMAPE (%) = 36.39	Benchmark performance	–
ResNet/LSTM		STLF	RMSE (kWh) = 0.263 SMAP (%) = 32.74%	More accurate and fast then individual LSTM	–

4.2.7 In Table 11 [41, 42], Multiple Hybrid Models Based on DNN Are Compared Using a Dataset of Independent System Operator of New England (ISO-NE)

See Table 11.

4.3 Techniques Based on Artificial Intelligence

4.3.1 In Table 12 [43], Two Hybrid AI-Based Techniques, Optimally Pruned Extreme Learning Machine (ANFIS) and Adaptive Network-Based Fuzzy Inference System (OP-ELM) Are Used for LF and Compared

See Table 12.

5 Conclusion

In this chapter, a review has been done of load forecasting models with a brief introduction of Electrical load forecasting and further moving toward its importance in current global power systems. There are many uncertainties faced during load forecasting which are discussed as factors affecting load forecasting. Therefore, using different parameters, a comparative review has been done of recent studies focusing on different techniques and models to obtain efficient and fast results. Parameters used to compare these models are: type of data used, type of load forecasting, standard errors: RMSE, NRMSE, MAE, significance/remarks, and their application. From this review, it is concluded that it is feasible to use individual models as LSTM, LR, RF, etc., for very short and short-term load forecasting. To forecast load for a longer period of time, models can be combined to form hybrid models according to their performance. Further studies can focus on hybrid models with combination of more than two models and with proper tuning of its parameters, these can be used for even long-term forecasting.

Table 11 Convolution of deep neural networks

Model	Data used	Types of load forecasting	Errors	Significance/remarks	Application/applicable to
Convolutional -LSTM	ISO-NE based dataset	STLF	MAE (kWh) = 118 MAPE (%) = 0.201	Outperforms other models used for comparison	Highly efficient for short and very short-term forecasting
Bidirectional LSTM		STLF	MAE (kWh) = 130 MAPE (%) = 0.443	Increase in training time may increase accuracy	–
LSTM		STLF	MAE (kWh) = 119 MAPE (%) = 1.049	–	–
Convolutional neural network (CNN)		STLF	MAE (kWh) = 133 MAPE (%) = 0.814	Better performance than time series models	Can be used for non-linear problems
Correlation Based convolution recurrent network (CCRN)		STLF	MAE (kWh) = 178 MAPE (%) = 0.634	Error reduction and require less training time	Can be used for electric commercial load

Table 7.12 Hybrid AI techniques: ANFIS and OP-ELM

Model	Data used	Types of load forecasting	Errors (kWh)	Significance/remarks	Application/applicable to
(OP-ELM)	Real dataset of large power consuming substation	STLF, MTLF	MAPE = 0.090344 MAE = 0.057076 RMSE = 0.077942	OP-ELM model out performs ANFIS model	Distribution stations
(ANFIS)		STLF, MTLF	MAPE = 0.088012 MAE = 0.060583 RMSE = 0.073518	Better performance then benchmarks models	Turning on/off electric power plants

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Load Forecasting Using Different Techniques

Arshi Khan and M. Rizwan

Abstract Load forecasting uses previous data from the electrical system to predict future electric load. For the planning and operation of the utility, precise models for forecasting the electric power load are required. Load forecasting can also be used to support an electric utility's future system operations, such as load switching, demand-side management, and identifying and forecasting energy consumption patterns. Electric charge prediction is critical in the electric power system because it determines when and how much generation, transmission, and distribution capacity must be arranged to match the predicted load without supply interruptions. As a result, the higher the quality of the forecast, the more accurate, dependable, and timely the results are. In this chapter, various methodologies used for load forecasting are discussed. With the help of artificial intelligence techniques, namely fuzzy logic, ANN, and ANFIS, the future load is predicted. All three methods are used for the data set considered, and the results are analyzed. The results of all three methodologies are studied and compared.

Keywords Short-term load forecasting · Artificial intelligence · Fuzzy logic

1 Introduction

With the rise in people's living standards, the share of cooling load, such as air conditioning, is increasing in summer load, posing a threat to the power system's safe operation and economic dispatch. Accurate daily load forecasting can provide a strong scientific basis for optimal unit combination, economic dispatch, electricity market transaction, and demand response in the implementation of national energy saving and emission reduction policies. The demand for power in India is steadily

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increasing. India's total installed capacity is 3,95,075 MW as of January 31, 2022. The reason for the rise in electricity usage is urbanization and population growth. It may be stated that this need will continue to rise in the future. Electricity is produced in response to demand [1].

Demand expectation is a significant angle in the advancement of any model for power planning, particularly in the present improving power framework structure. The type of the interest relies upon the kind of preparation and precision that is required. Depending upon the time locale of planning strategies, the forecasting of load can be classified into the following three types specifically:

- Short-term load forecasting (STLF): In this method, generally, the time period ranges from an hour to a week. It can direct us to surmised load flow and then lead to making choices that can block excess loading. Transient determining is utilized to give mandatory data for managing system of day-to-day activities and unit responsibility.
- Medium-term load forecasting (MTLF): In this method, the period of time range is from a week to a year. The figures for various time horizons are significant for various tasks inside a utility organization. Medium-term estimating is utilized to plan fuel supplies and unit the board.
- Long-term load forecasting (LTLF): In this method, the time range is more than a year. It is utilized to supply electric service organization with précised expectation of future requirements for extension, hardware buys, or staff employing.

In [2], importance of load forecasting and issues regarding load forecasting are focused. Various methodologies of artificial intelligence that can be used in forecasting are explained like fuzzy, ANN, statistical, spatial, etc. It highlights the importance of these various intelligent system approaches and helps in recognizing various aspects of research in these methods. In [3], priority vector-based technique for load forecasting is used. Records of almost two years of load at every hour and weather are extracted, and the relation between them is drawn and categorized based on that. It is an adaptive technique as it generates relationship coefficient between weather parameters and load continuously. As these relations change from time to time, it automatically updates the changed coefficient between these two parameters. It is used to predict forecast of load of one week. In [4], knowledge-based expert system is used for short-term load forecasting (STLF). The expert system developed in this method is written using 5 years of historical data in prolog. Distinct load shapes and their load calculations are done. Various categories of load usage according to the observation are set like low level of load during Chinese New Year or at the time of typhoon. With the help of these observations, new rules or information are made or set for the purpose of short-term load forecasting. In [5], linear regression-based method or model used for STLF is described. This model takes care of many areas such as innovative model of building, with the help of which weighted least squares in linear regression techniques estimation of parameters are done, with the use of which reverse errors-in-variables techniques effect of potential errors on load forecasts can be relieved, and to differentiate between daily time-independent peak load forecast and maximum hourly peak load forecast from negative bias.

In this chapter, three models are developed for short-term load forecasting using fuzzy logic, ANN, and ANFIS.

2 Fuzzy Logic-Based Forecasting

The fuzzy logic concept was introduced by Professor Lotfi A. Zadeh. Truth is certainly not an outright idea. Fuzzy logic gives an approach to address levels of conviction. It is a technique for thinking that looks like human thinking. It is a problem-solving tool that falls somewhere between classical logic's precision and the real world's inherent imprecision. Several fuzzy logic-based algorithms have been established in recent years to interpret picture data with vagueness and ambiguity due to the acquisition phase, as well as imprecise and ill-defined knowledge about the image contents. Fuzzy sets, which are the main parts of fuzzy logic, can be used to handle the imprecision in an image stored in the pixels. Vague ideas such as sharp boundaries, excellent contrast, high saturation, bright red, and so on can be recognized qualitatively by human reasoning and articulated in a formal way using fuzzy logic, allowing a machine to emulate human reasoning.

2.1 Architecture of Fuzzy Logic

Figure 1 shows the block diagram of fuzzy logic. The methodology of FL impersonates the method of dynamic in people that includes all middle of the road prospects between computerized values YES and NO. The four main parts can be explained as follows:

(1) Fuzzifier: The method of fuzzification involves converting crisp inputs into fuzzy sets defined on the input space. The component of the system that

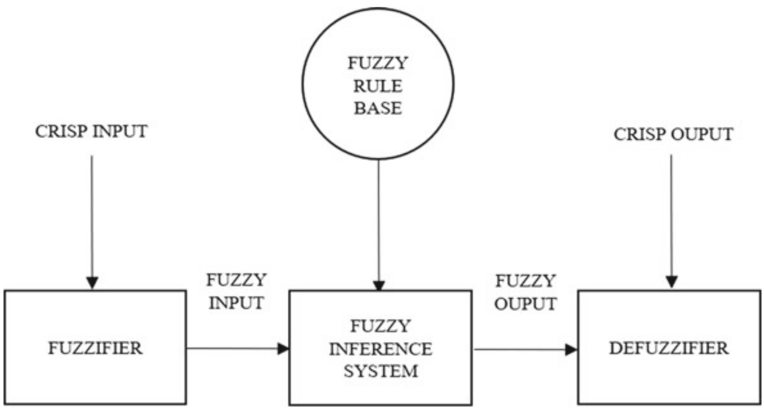

Fig. 1 Fuzzy logic block diagram

performs this procedure is known as a fuzzifier. In this stage, a fuzzification function is used to express the measurement uncertainty for each input variable. The fuzzification function's objective is to interpret measurements of input variables, each of which is expressed as a real number, as more realistic fuzzy approximations of those real numbers.

(2) Fuzzy rule base: It contains the course of action of rules and the IF–THEN conditions given by the experts to direct the unique structure, in view of linguistic information. Late upgrades in feathery speculation offer a couple of fruitful strategies for the arrangement and tuning of fuzzy controllers. Most of these headways decline the number of fuzzy rules.

(3) Fuzzy inference system: It chooses the organizing with level of the current fuzzy information concerning every norm and picks which rules are to be ended by the data field. At that point, the ended standards are joined to outline the control exercises.

(4) Defuzzifier: A crisp value is frequently required as the output of a fuzzy rule-based system, which is a necessity in many engineering challenges, such as fuzzy control applications. A defuzzification stage is required in these circumstances to achieve a crisp output from the fuzzy output generated by rule inference.

Membership functions allow us to graphically represent a fuzzy set. In the membership functions, The x axis represents the universe of discourse, whereas the y axis represents the degrees of membership in the [0, 1] interval.

Membership functions that could be classified into two groups: those made up of straight lines being **"linear"** ones, and the **"curved"** or **"nonlinear"** ones. Some of the most common membership functions are listed as follows:

(1) Triangular function.
(2) Trapezoidal function.
(3) Gaussian function.

2.2 *Fuzzy Logic Model*

Generalized flowchart for fuzzy is shown in Fig. 2. The load consumed in a location is recorded every minute and the average is calculated every 15 minutes. The data of input and output is a normalized value that is scaled down in the range of 0.1–0.9. It is done to avoid convergence problem. The normalized values of the data can be seen in Table 1. Fuzzy logic is basically the general Boolean logic that is used in design of digital circuits. It takes only two values, i.e., false (0) or true (1). But in this, the input can take the values in between 0 and 1 also. It chips away at the degrees of potential result for contribution to attain the definite output. The actual data is scaled down using the equation below:

$$L_S = \frac{(Y_{\max} - Y_{\min})}{(L_{\max} - L_{\min})}(L - L_{\min}) + Y_{\min} \tag{1}$$

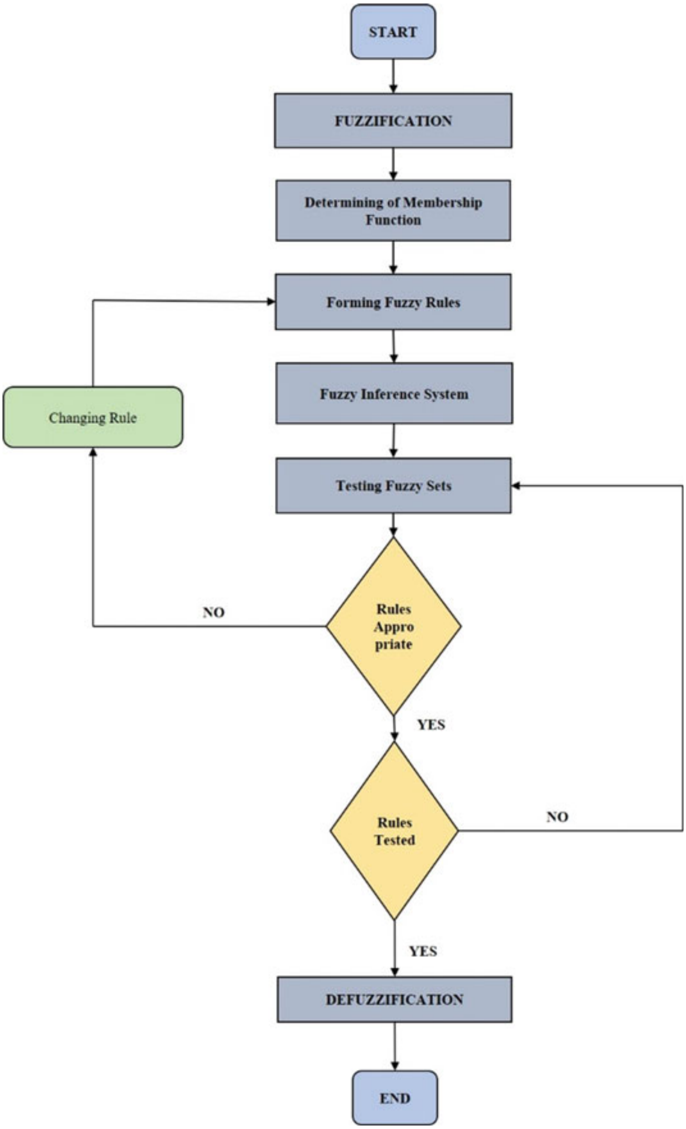

Fig. 2 Flowchart for fuzzy logic

where

Y_{max} is 0.9;
Y_{min} is 0.1;
L_{max} is maximum load value;
L_{min} is minimum load value;
L is load to be converted;
L_S is normalized value.

Table 1 Normalized value

Time	Inputs						Output
	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	
00:15	0.3	0.34	0.44	0.43	0.48	0.50	0.54
00:30	0.27	0.30	0.41	0.4	0.48	0.47	0.54
00:45	0.27	0.30	0.41	0.34	0.47	0.39	0.54
01:00	0.26	0.27	0.39	0.34	0.40	0.49	0.54
01:15	0.26	0.27	0.37	0.34	0.40	0.49	0.54
01:30	0.25	0.27	0.37	0.34	0.40	0.49	0.51
01:45	0.25	0.27	0.38	0.34	0.40	0.49	0.39
02:00	0.26	0.27	0.37	0.34	0.40	0.43	0.39
02:15	0.25	0.27	0.37	0.34	0.40	0.38	0.39
02:30	0.26	0.27	0.37	0.34	0.40	0.38	0.39
02:45	0.25	0.27	0.37	0.34	0.40	0.38	0.39
03:00	0.26	0.27	0.37	0.34	0.39	0.38	0.39
03:15	0.25	0.27	0.37	0.34	0.35	0.38	0.39
03:30	0.25	0.24	0.37	0.34	0.35	0.38	0.39
03:45	0.26	0.25	0.37	0.34	0.35	0.38	0.39
04:00	0.26	0.26	0.33	0.34	0.35	0.38	0.39
04:15	0.26	0.24	0.33	0.32	0.35	0.38	0.39
04:30	0.25	0.24	0.33	0.30	0.35	0.37	0.39
04:45	0.25	0.25	0.33	0.30	0.35	0.35	0.39
05:00	0.25	0.25	0.33	0.31	0.35	0.35	0.39
05:15	0.26	0.27	0.33	0.31	0.38	0.35	0.39
05:30	0.27	0.27	0.33	0.31	0.38	0.35	0.39
05:45	0.27	0.27	0.33	0.31	0.35	0.35	0.39
06:00	0.27	0.27	0.33	0.31	0.35	0.35	0.39
06:15	0.26	0.27	0.30	0.31	0.35	0.35	0.36
06:30	0.25	0.27	0.34	0.31	0.32	0.32	0.35
06:45	0.25	0.33	0.33	0.27	0.33	0.36	0.35
07:00	0.26	0.36	0.33	0.33	0.41	0.45	0.44
07:15	0.26	0.35	0.33	0.38	0.41	0.45	0.45
07:30	0.27	0.35	0.34	0.37	0.43	0.46	0.46
07:45	0.26	0.35	0.40	0.38	0.45	0.46	0.48
08:00	0.26	0.35	0.42	0.38	0.48	0.47	0.52
08:15	0.28	0.35	0.42	0.41	0.51	0.50	0.53
08:30	0.28	0.34	0.46	0.42	0.53	0.53	0.56
08:45	0.29	0.31	0.48	0.46	0.55	0.55	0.61

(continued)

Table 1 (continued)

Time	Inputs						Output
	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	
09:00	0.30	0.31	0.54	0.48	0.57	0.57	0.63
09:15	0.31	0.31	0.51	0.46	0.61	0.61	0.56
09:30	0.35	0.29	0.62	0.43	0.47	0.70	0.64
09:45	0.30	0.38	0.75	0.61	0.78	0.73	0.68
10:00	0.40	0.45	0.77	0.66	0.8	0.73	0.79
10:15	0.42	0.46	0.77	0.69	0.8	0.66	0.84
10:30	0.43	0.45	0.77	0.73	0.84	0.69	0.87
10:45	0.43	0.46	0.81	0.77	0.84	0.69	0.88
11:00	0.44	0.33	0.81	0.79	0.87	0.72	0.88
11:15	0.44	0.40	0.81	0.80	0.89	0.82	0.88
11:30	0.44	0.40	0.81	0.80	0.88	0.89	0.88
11:45	0.44	0.39	0.81	0.78	0.9	0.88	0.88
12:00	0.45	0.36	0.83	0.75	0.88	0.86	0.87
12:15	0.44	0.38	0.83	0.73	0.85	0.84	0.86
12:30	0.43	0.37	0.81	0.73	0.87	0.83	0.84
12:45	0.43	0.37	0.79	0.78	0.87	0.82	0.8
13:00	0.43	0.37	0.79	0.79	0.87	0.82	0.78
13:15	0.43	0.35	0.77	0.76	0.81	0.82	0.75
13:30	0.40	0.35	0.77	0.67	0.67	0.78	0.74
13:45	0.39	0.35	0.79	0.61	0.77	0.78	0.75
14:00	0.38	0.36	0.78	0.59	0.79	0.79	0.74
14:15	0.38	0.39	0.78	0.56	0.79	0.79	0.77
14:30	0.38	0.35	0.76	0.60	0.79	0.81	0.85
14:45	0.38	0.43	0.75	0.73	0.75	0.83	0.85
15:00	0.38	0.46	0.69	0.73	0.74	0.83	0.83
15:15	0.38	0.25	0.62	0.76	0.74	0.81	0.80
15:30	0.38	0.39	0.48	0.75	0.73	0.78	0.78
15:45	0.35	0.35	0.44	0.76	0.70	0.76	0.73
16:00	0.32	0.38	0.44	0.66	0.83	0.69	0.67
16:15	0.31	0.38	0.44	0.60	0.55	0.54	0.51
16:30	0.31	0.1	0.44	0.47	0.54	0.49	0.44
16:45	0.36	0.28	0.44	0.42	0.55	0.45	0.40
17:00	0.02	0.26	0.43	0.43	0.57	0.45	0.40
17:15	0.36	0.25	0.40	0.40	0.42	0.47	0.43

(continued)

Table 1 (continued)

Time	Inputs						Output
	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	
17:30	0.36	0.27	0.37	0.38	0.42	0.45	0.43
17:45	0.36	0.24	0.37	0.36	0.40	0.41	0.44
18:00	0.36	0.24	0.37	0.36	0.39	0.41	0.44
18:15	0.29	0.25	0.35	0.35	0.33	0.39	0.41
18:30	0.26	0.27	0.37	0.32	0.33	0.38	0.40
18:45	0.26	0.20	0.45	0.32	0.33	0.38	0.37
19:00	0.3	0.26	0.48	0.32	0.33	0.41	0.37
19:15	0.31	0.25	0.48	0.32	0.33	0.49	0.38
19:30	0.31	0.26	0.48	0.33	0.35	0.46	0.38
19:45	0.28	0.34	0.48	0.36	0.37	0.47	0.40
20:00	0.27	0.36	0.49	0.43	0.37	0.46	0.42
20:15	0.28	0.39	0.52	0.43	0.37	0.46	0.41
20:30	0.28	0.38	0.52	0.43	0.37	0.47	0.38
20:45	0.29	0.35	0.49	0.43	0.37	0.50	0.40
21:00	0.29	0.36	0.49	0.45	0.38	0.53	0.50
21:15	0.29	0.36	0.49	0.47	0.41	0.53	0.53
21:30	0.29	0.35	0.51	0.47	0.41	0.53	0.56
21:45	0.30	0.35	0.52	0.47	0.41	0.53	0.56
22:00	0.30	0.29	0.52	0.47	0.41	0.53	0.57
22:15	0.30	0.28	0.52	0.47	0.41	0.53	0.56
22:30	0.30	0.31	0.51	0.47	0.41	0.53	0.56
22:45	0.30	0.38	0.49	0.47	0.41	0.53	0.53
23:00	0.30	0.38	0.49	0.46	0.41	0.53	0.52
23:15	0.30	0.38	0.43	0.46	0.43	0.53	0.52
23:30	0.30	0.38	0.40	0.44	0.54	0.53	0.52
23:45	0.30	0.38	0.40	0.43	0.48	0.53	0.51
00:00	0.27	0.38	0.40	0.4	0.48	0.53	0.49

Fuzzy methodology that is put forward can be utilized as a guide to forecasting the heaps with various time arrangements. An accurate fuzzy system can be made by dividing into various intervals. The basic fuzzy logic model used for STLF for the data can be seen in Fig. 3. The span of input as well as output is divided into thirteen triangular membership functions that is presented in Fig. 4.

The triangular membership functions are utilized where the help of the participation work is settled based on the gathered information. The arrangement of the creation rules depends on the basic semantic learning and is the essential premise for the forecast model. The output of the model will exclusively rely upon this, and

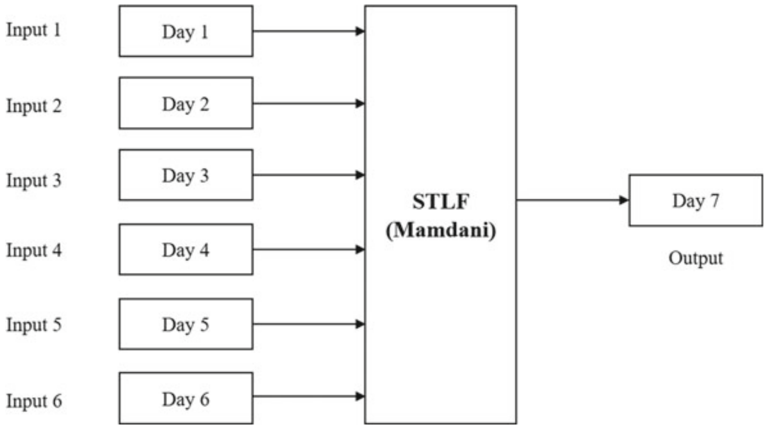

Fig. 3 Model of fuzzy logic for STLF

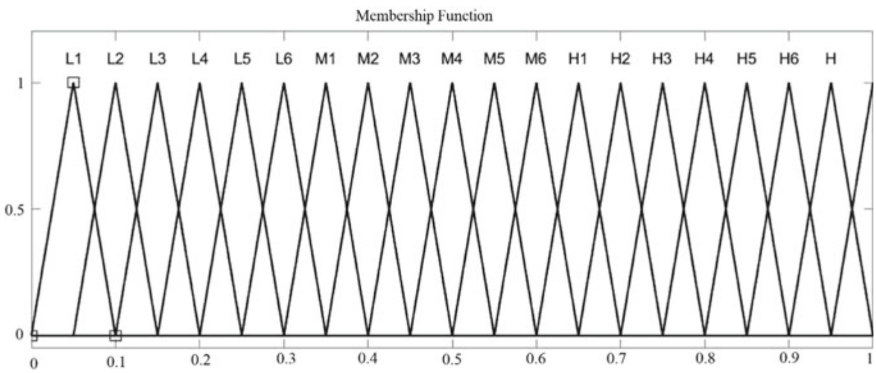

Fig. 4 Input and output triangular membership function

subsequently after primer investigation of the informational collection, the accompanying creation rules are utilized; anyway, the equivalent might be distinctive for another arrangement of information. Together the triangular membership functions as well as fuzzy rules are intended to give a simpler technique in which we can implement instinct and experience directly into a PC program.

After the crisp input is applied with logical reasoning or through the fuzzy inference system, an output is obtained to which the defuzzification process can be applied and the crisp output can be obtained. The output obtained from the model is then compared to the actual load which can be seen in Fig. 5. One of the outputs for the 28th rule is seen in Fig. 6.

Then, absolute relative error (ARE) is calculated with the help of formula given below:

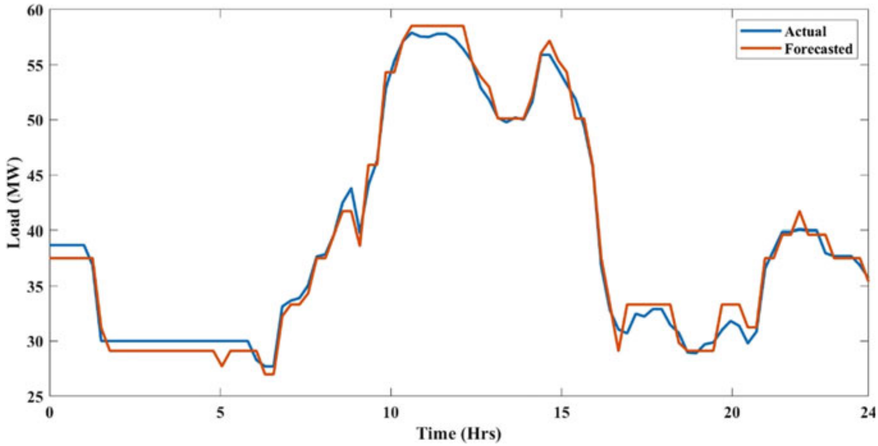

Fig. 5 Actual load versus forecasted load using FL

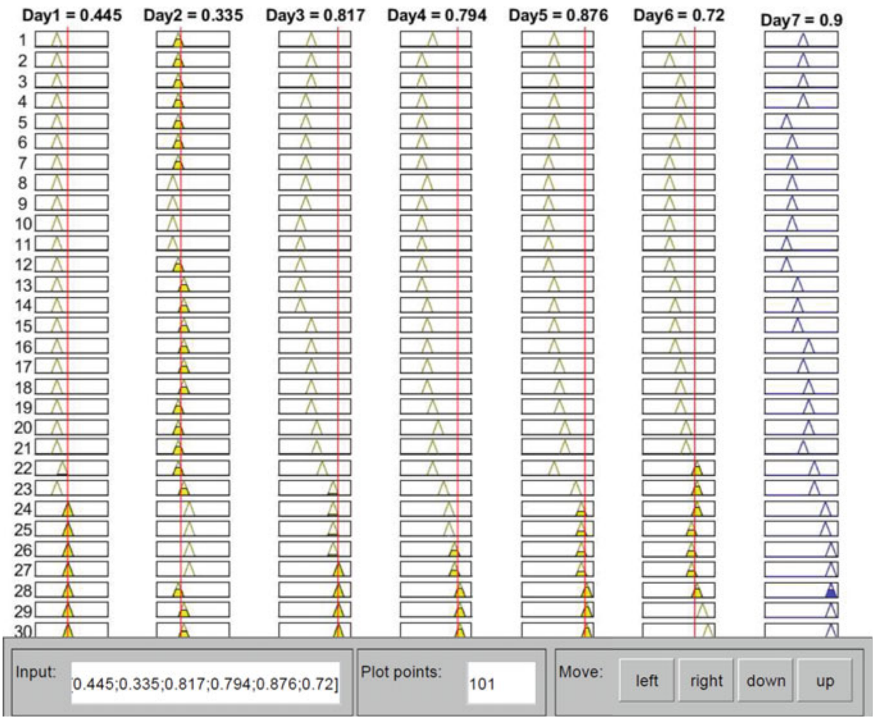

Fig. 6 Rule viewer for 28th rule

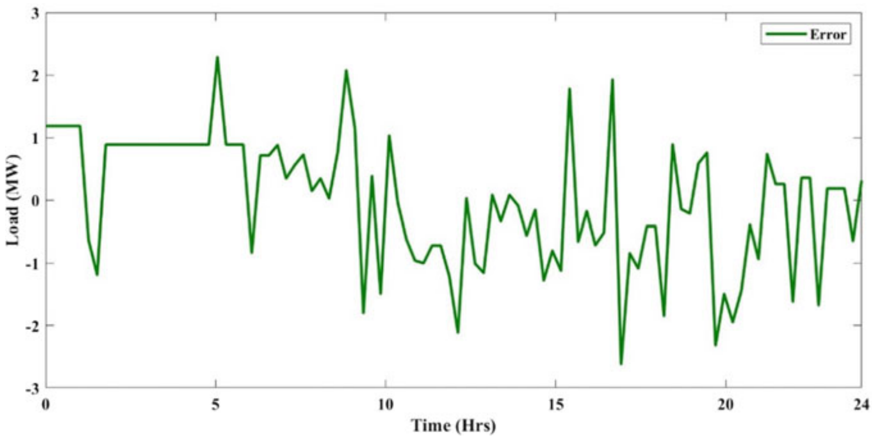

Fig. 7 Error obtained in fuzzy

$$\text{ARE} = \frac{P_{\text{desired}} - P_{\text{forecasted}}}{P_{\text{desired}}} \times 100 \qquad (2)$$

where P_{desired} is the target load and $P_{\text{forecasted}}$ is the forecast load through fuzzy logic model for STLF. The error obtained is observed in Fig. 7.

The comparison is done to check the accuracy of the fuzzy logic model developed for the STLF. It can be observed that the load forecasted is nearby the actual demand data. It was observed that minimum ARE is 0.052% and maximum ARE is 8.514%. The average absolute relative error calculated is 2.376%. It can be concluded that the error is low. Hence, the fuzzy model developed for the purpose of STLF for this data is accurate.

3 Artificial Neural Network

It is also known as neural network (NN). It is a machine which acts like human brain with learning capacity and speculation as its attributes. ANNs make them learn capacities that empower them to deliver better outcomes as more information opens up. It is the establishment of AI and tackles issues that would demonstrate outlandish or troublesome by human or measurable norms. They are basically nonlinear mathematical processing networks. They are being used in fields like image recognition, load forecasting, speech recognition, energy consumption prediction, data retrieval, and mine dam water level prediction and monitoring. Because of their ability to work on complicated and nonlinear systems, artificial intelligence methods for predicting complex and ambiguous models have grown popular. Artificial neural networks (ANNs) are based on the operation of biological neural networks and can learn in a similar way to humans. It has three layers: an input layer that accepts data, a hidden layer that processes data between the input and output levels, and an output layer that outputs the data (which sends computed data). Each layer is made up of neurons that process the input parameters and produce an output, with a weight factor applied to the connections between layers.

In [6], ANN is studied in context of its strength in field of power system and its application. Also, its application in various problems of power system is briefly discussed. An overview of ANN-based models for STLF is presented in [7]. Review of paper published during 1991 and 1999 is done. These papers that are reviewed are application of NN used for STLF purpose. Each paper is critically reviewed to properly understand the use of NN in forecasting. A further developed NN approach is produced for STLF purpose in [8]. An approach that is befitting for selection of training cases in the NN is suggested. This approach has benefit of circumventing the issue of holidays and sudden changes in weather patterns, which makes it difficult for training of network. Additionally, an improved algorithm for neural network is presented. In [9], the practicality of utilizing simple NN for STLF is researched. The combination of nonlinear and linear neural network is created. The estimates are computed utilizing weights that are re-estimated using recent observations.

3.1 Architecture of Artificial Neural Network

ANNs are made out of different nodes, which mimic natural neurons of human mind. The neurons are associated with connections, and they communicate with one another. The hubs can take input information and perform straightforward procedure on the information. The outcome of these activities is passed to different neurons. The yield at every hub is called its initiation or node value. It consists of three layers:

(i) Input layer: It is the first layer. It enters the external input data in the network.
(ii) Hidden layer: It is the second layer. It is the layer between output and input. All sorts of calculation are performed in this to determine any pattern or hidden feature.
(iii) Output layer: It is the final layer. After going through some transformation series in hidden layer, it provides an output which is conveyed by this layer.

The basic structure is seen in Fig. 8.

3.2 ANN Method for Load Forecasting

Using the algorithm discussed through flowchart in Fig. 9, the forecasted load data for the seventh day for the location is generated through ANN. With the help of "nftool" in MATLAB, ANN model is developed. Feed forward network type of ANN is used here. Training of network is done by using "Levenberg–Marquardt backpropagation algorithm".

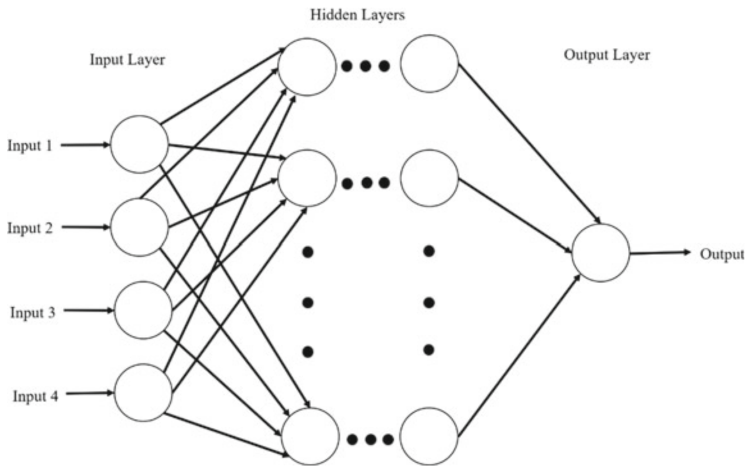

Fig. 8 Basic structure of ANN

The input layer includes information that the network must use during the learning process, like target data that the network must imitate. The weights are modified during.

The training process to provide the best outcomes. The network's input and target vectors are divided into three groups at random as follows:

- 60% will be used for training.
- 20% for validating that the network is generalizing and terminating the training process before overfitting or terminating training when generalization has reached its limit.
- The 20% was utilized as a completely independent network generalization test. This has no bearing on training; instead, it serves as an independent indicator of network performance during and after training (Fig. 10).

Figure 11 represents the regression plot obtained during ANN model training and testing. Figure 12 is comparing of actual load and forecasted load from ANN model. Figure 13 is the error plot obtained by ANN.

The average absolute relative error calculated is 2.913%. It is slightly more than fuzzy model error but accurate enough for the purpose of STLF.

4 Adaptive Neuro-Fuzzy Interference System

ANFIS can address any sort of nonlinear and complex issues successfully by adding the benefits of ANN and fuzzy. It merges the mathematical and linguistic information by using fuzzy methods. It additionally utilizes the ANN's capacity of classification of data and identifies the pattern. Also, the ANFIS causes less retention error and is

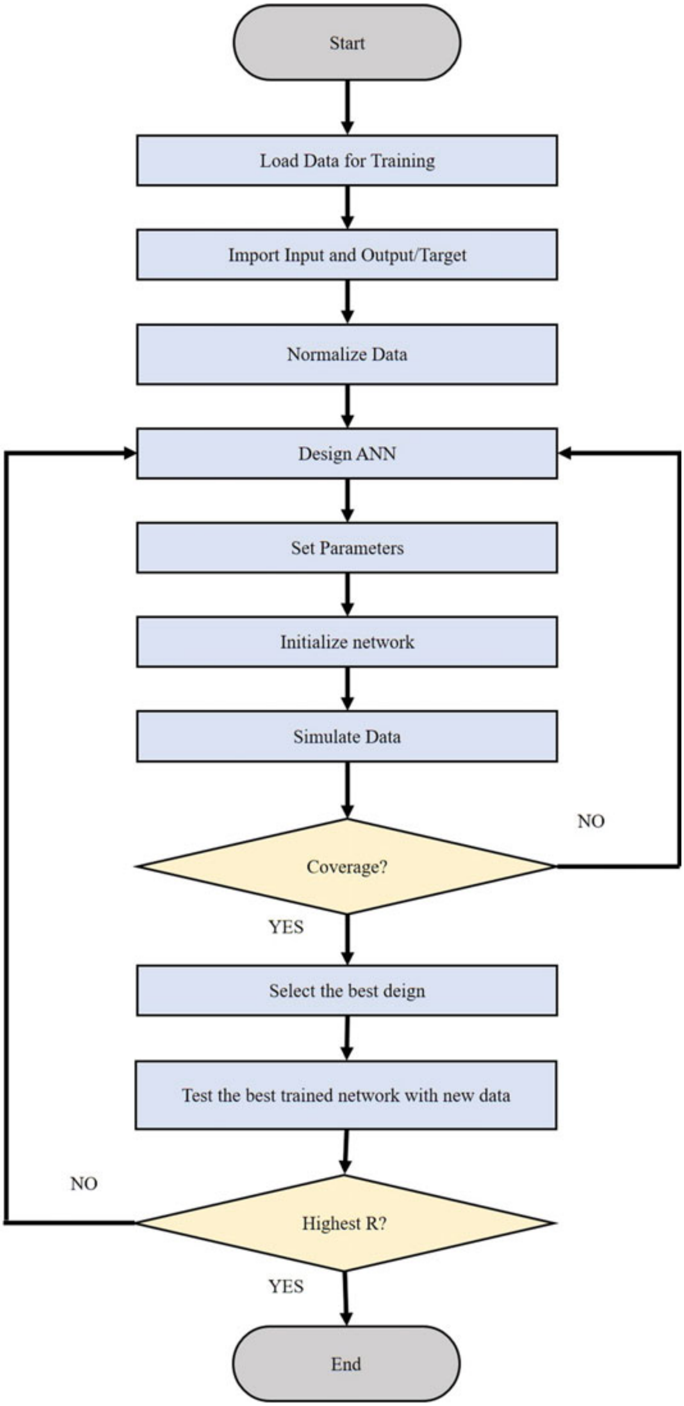

Fig. 9 Flowchart of ANN algorithm

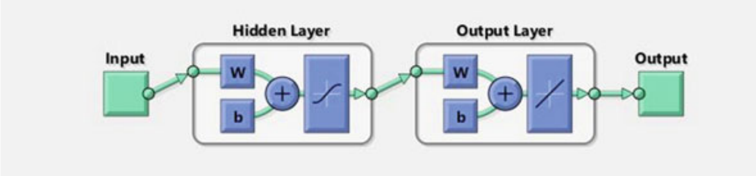

Fig. 10 ANN model in MATLAB

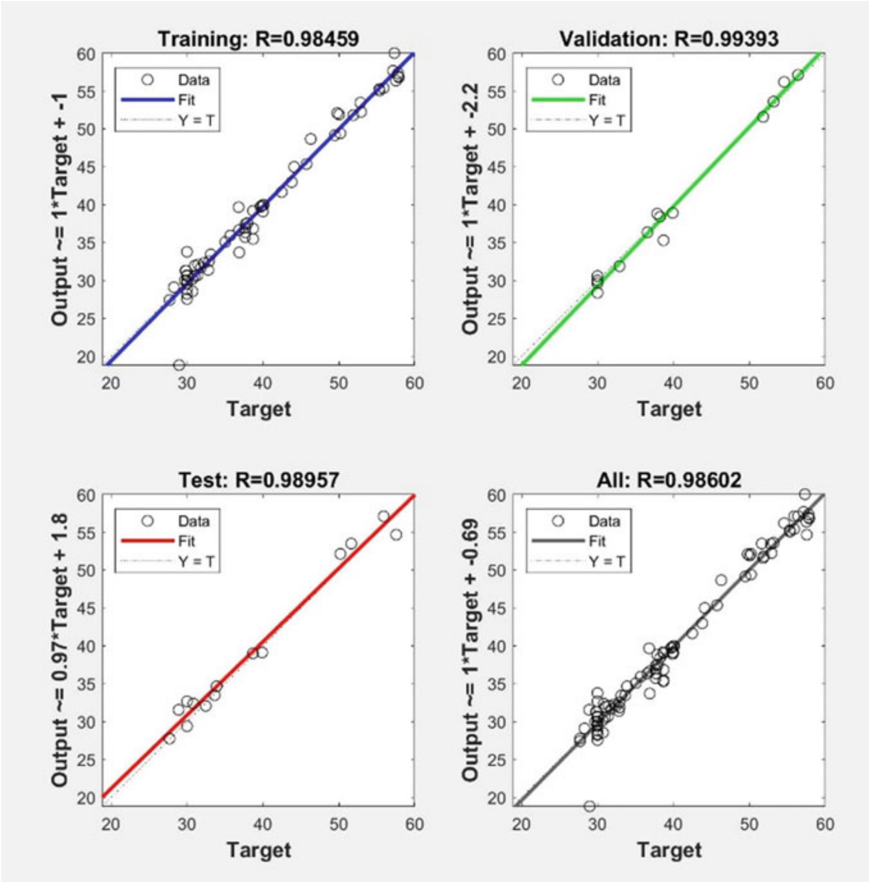

Fig. 11 Regression plot while implementing ANN model

more noticeable to user in comparison with ANN. It is a combination of both ANN and fuzzy logic (FL). Hence, it has advantages of both the methods overcoming their flaws. FL cannot gain any information from the data. ANN has absence of information representability and logic.

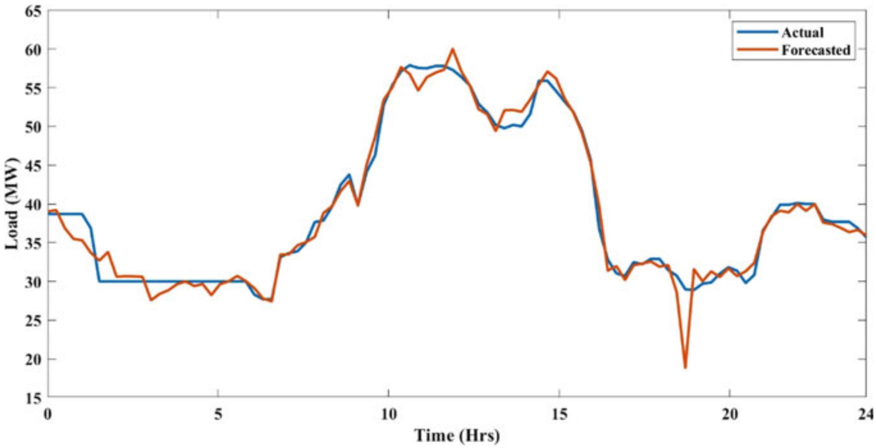

Fig. 12 Actual versus forecasted load through ANN

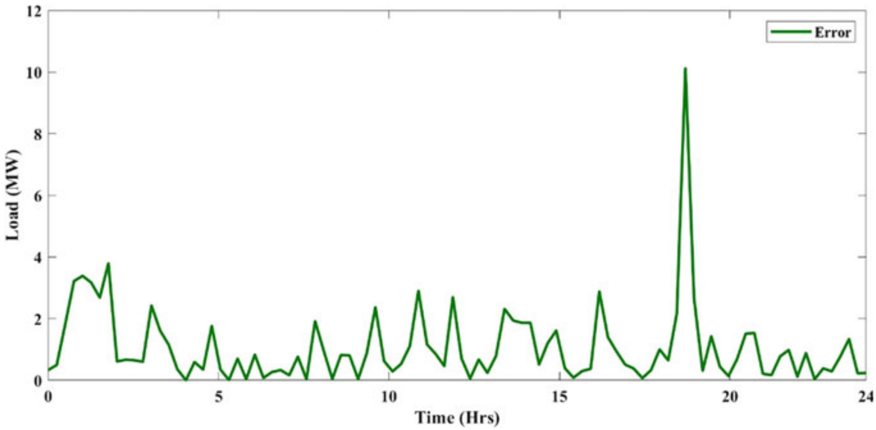

Fig. 13 Error obtained using ANN

In [10], adaptive neuro-fuzzy inference system (ANFIS) is used for the purpose of studying STLF design. In this paper, consumed load is forecasted with the help of multi-ANFIS. Sections of the presenting model are into the multi-ANFIS which includes maximum and minimum temperature, date of day, condition of climate, and consumed load of previous day, and its output is the forecast of load consumption of power. In [11], ANFIS model is developed for short-term load forecasting purpose. It is the combination of both fuzzy and ANN. Factors like data types and weather, etc., are used in this model. The training of the model is done by historical load data. ANFIS-based approach of load forecasting is used for small regions with low consumption in [12].

4.1 Architecture of ANFIS

ANFIS consists of five layers of neurons as shown in Fig. 14. Every layer has their own behavior. Layers 2, 3, and 5 consist of constant behavior, whereas layer 1 and layer 4 have varying parameters, in these modifications are done for training. These five layers are as follows:

(1) Layer 1—Fuzzification

In this layer, process known as fuzzification is carried out. Degrees in which every input is belonged to fuzzy space are given the values in between 0 and 1. Every node in this layer is adaptive node. The input and output relation of this node can be given as follows:

$$O(1, i) = \mu_{\mathrm{A}i}(x), \quad i = 1, 2 \tag{3}$$

(2) Layer 2—Fuzzy rule

Every node is fixed and addressed with a rule. Every node of this layer duplicates the input signal which can show degrees to which the sources of incoming signal fulfill the membership function. The result of the information signs to every node of this layer addresses the terminating strength of a rule. The output for this can be defined as follows:

$$O(2, i) = \mu_{\mathrm{A}i}(x)\mathrm{X}\mu_{\mathrm{B}i}(y), \quad i = 1, 2 \tag{4}$$

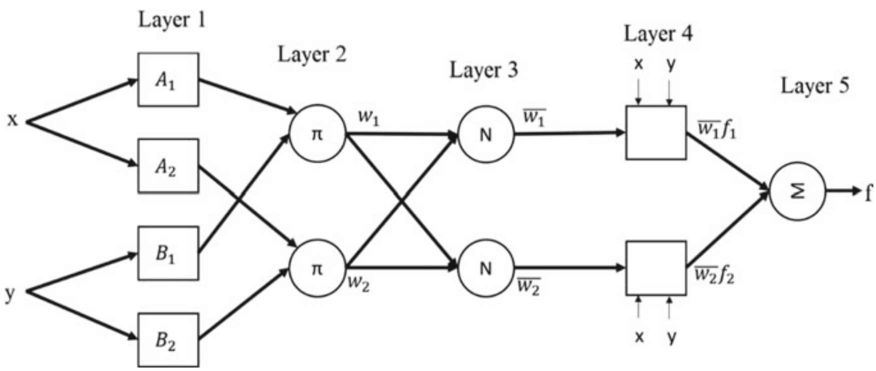

Fig. 14 Basic structure of ANFIS

(3) Layer 3—Normalization

In this layer, fixed nodes are named as N. Output in this layer is normalization of the weight work or summation of every rule firing strength as follows:

$$O(3, i) = w_i' = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \tag{5}$$

(4) Layer 4—Defuzzification

Every node registers the weighted subsequent value of every rule which addresses the contribution of every rule to the output overall. These are adaptive nodes other than the nodes in fuzzy layer. In this layer, nodes calculate output of rules base on subsequent parameters as follows:

$$O(4, i) = w_i' f = w_i'(p_i x + q_i y + r_i), \quad i = 1, 2 \tag{6}$$

(5) Layer 5—Output

It is the final layer. By summing all the incoming signals, it provides the output as below:

$$O(5, i) = \sum_{i=1}^{2} w_i' f_i, \quad i = 1, 2 \tag{7}$$

4.2 ANFIS Model for Load Forecasting

For the development of ANFIS model, MATLAB 2018 software is used. With the help of “anfisedit”, ANFIS model is developed. The methodology’s training section is based on a system that collects data from the plant’s database on a regular basis in order to analyze the data and find potential energy pattern behaviors. Approximately, 70% data is trained and 30% data is tested in this model. Using the algorithm discussed through the flowchart in Fig. 15, the forecasted load data for the seventh day for the location is generated through ANFIS.

Figure 16 shows the comparison of forecasted load from ANFIS model and actual load recorded. Figure 17 is the error plot obtained by ANFIS.

The average absolute relative error calculated is 1.953%. It is less than fuzzy and ANN model. It can be said that the model developed is accurate for load forecasting.

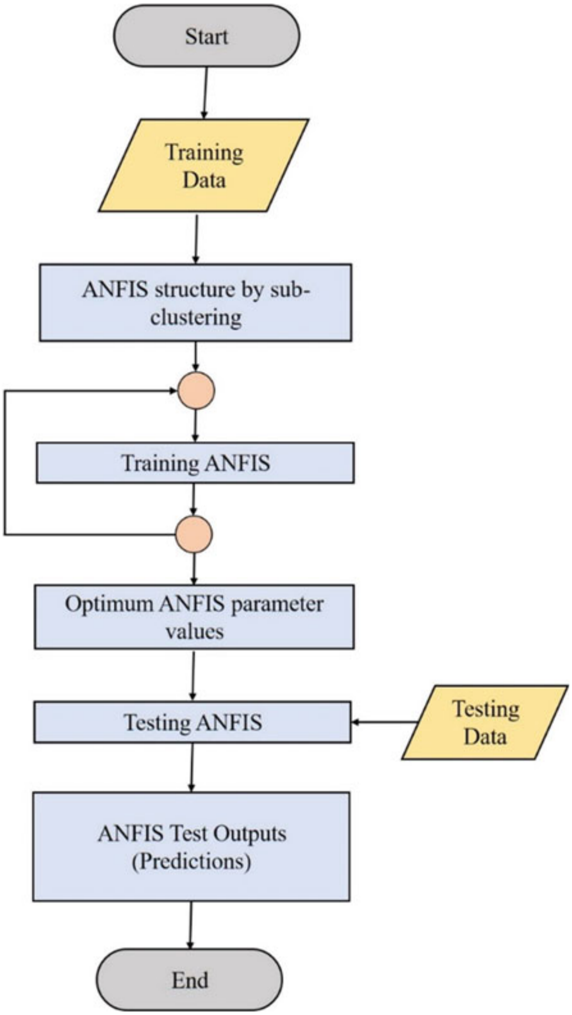

Fig. 15 Flowchart for ANFIS algorithm

5 Conclusion

The importance of short-term load forecasting is increasing with increase in the utilization of electricity. In electricity load forecasting, machine learning techniques are demonstrating to be quite useful. These are frequently being used as one of the most forward-looking approaches during the time of generation of electricity, market planning activities, and also in planning for development in the distribution network.

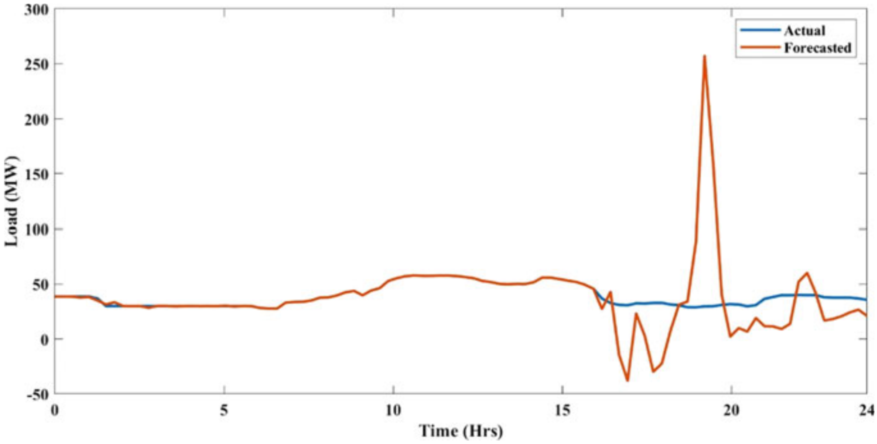

Fig. 16 Actual versus forecasted load through ANFIS

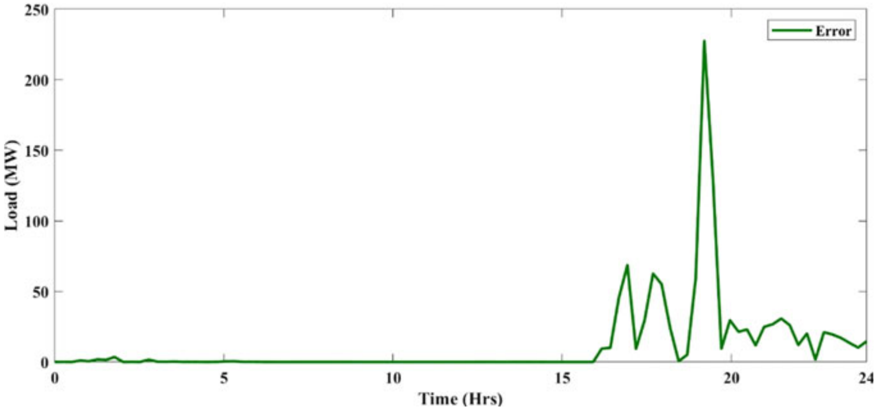

Fig. 17 Error obtained using ANFIS

In fuzzy model, it is observed that at 12:30 pm the accuracy of the model developed is 100%. The rest are nearby values for the actual load. The average absolute relative error calculated is 2.376%. So, it can be concluded that the model developed for the STLF is quite accurate (Fig. 18).

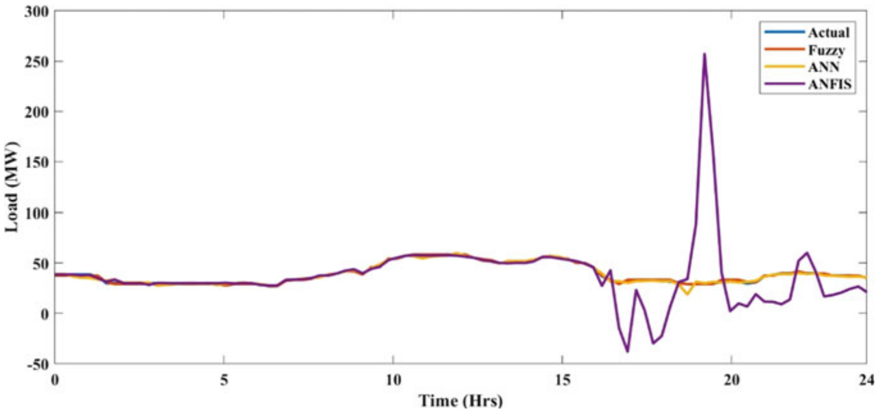

Fig. 18 Comparison of actual load with all the techniques used

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Time Load Forecasting: A Smarter Expertise Through Modern Methods

Trina Som

Abstract Electricity is a necessary aspect of modern life, and it benefits us in a variety of ways. Electricity is a part of daily living of human race, which includes basic lighting, cooling, heating, cooking, refrigeration, as well as for operations of electronic appliances, online-based systems, transportations, and medical purposes. With growing awareness towards effective and green energy production, forecasting of accurate load demand has become the most vital part in today's power sectors. Suppliers of energy and others involved in electric energy's generation, distribution, and transmission along with marketing, rely heavily on the demand estimates. Electricity demand estimates are used to guide investment decisions in power generating transmission, distribution, and markets, as well as network infrastructure. Forecasts are also important for development experts as well as power utilities, energy policymakers, and private investors. Forecasting of electric power demand is regarded as one of the most important aspects of economic operation of power systems, which serves as a significant cost-cutting potential for power utilities or companies. Many research resulted in achievement of maximum savings when control operations, fuel allocations, economic dispatch, unit commitments are made on the basis of proper load forecasting. Hence, development of exact models for projecting the electricity demand is critical for functioning and planning of utility companies. Calendar seasonal information, wind speed, air temperature, history knowledge of load pattern, air temperature, wind speed, geographically information, and economic events are all aspects that influence prediction or forecasting of the load. The forecasting of load on timely basis has mainly been classified into short-term, medium-term, and long-term forecasts. Different models with different modes and constraining parameters, needs proper controlling methods. These methods are generally known as traditional forecasting technique, modified traditional technique, and modern techniques. Though the conventional methods are able to consider the above-mentioned aspects on time series forecast, but it often takes a longer time and complicated ways to predict the desire value. Unlike the conventional methods, the hybrid models, are capable of

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adapting to the fluctuations in the raw value of electric load data. The hybrid techniques results in a better performance and higher accuracy in forecasting. By fusing the best of statistics and machine learning techniques, the hybrid methods promise to advance time series forecasting. The basic concepts of hybrid techniques in forecasting lies in compensating the weakness of one method with strength of other. However, this field of research is essential to create the statistical significance of the existing data, by analyzing existing methods, initiating generalized research queries, and further exploring areas of possible improvements.

Keywords Load forecasting · Short term · Long-term · Optimization · Grasshopper optimization method

1 Introduction

Electricity forecasting is an important part of the power grid, which has piqued academic interest. Forecasting allows for well-versed and efficient responses to demand for electricity. However, there are many models for forecasting which are available thus making the unskilled researchers to choose the right one.

Forecasting models are frequently employed in a variety of fields, including as stock market movements with forecasting or stock market indexes [1]. In business, it's used to schedule employees, manage inventories, and forecast demand, while in meteorology, it's used to forecast weather [1], and in many economic estimations in social and professional events.

Power plant control relies heavily on forecasts and the exchange of electrical power in linked systems [2]. Proper forecast aids the planners in comprehending the impact of several factors influencing energy consumption, thereby providing better results with good decisions [3]. Prediction of electrical load demand is an important part of the power industry's planning. It is important for the function of electrical power grids [3]. Electrical load demand projections is closely linked to the economic growth, as well as national security and society's day-to-day operations [4]. As a result, the accuracy of electric load forecasting and scheduling of maximum generation of power is crucial for power system management. On a temporal scale, forecast includes short-term predictions, such as for keeping a balance between the prediction on long term basis and electrical power generation, and long-term predictions, such as for building the maximum capacity, return on investment evaluations, and revenue studies [5]. Various forecasting models or frameworks have been explored and tested to aid in the easier acquisition of results in the sphere of business and marketing [6]. Despite the fact that several forecasting models and methodologies have been developed to calculate reliable load forecasts, selecting an acceptable. It is difficult to develop a forecasting model for a given energy network, and none of these, however, can't be used for all demand patterns [7]. Hence emerging of new and modified forecasting methods are the prime need of the society at the present time period.

2 Types of Electrical Load Forecasting

For proper planning and functioning of a power utility firm, a good model for projecting electric power consumption is required. Accurate prediction of load is critical in assisting an electric utility when making key decisions about power, switching of load, control of voltage, re-configuration of network, and structure development [8]. Among various forecasting models, the most common type of classification is done on the basis of time. Long, medium-and short-term forecasting models are the types in this genre.

2.1 Long Term

This form of forecasting is usually done over a number of years (of about twenty years approximately). This form of projection is crucial for long-term planning, generating new building, and the development of the power supply and distribution system. In terms of annual numbers, long-term power demand may increase, and the temporal load profile's contour could also change. With the need of long-term load forecast precision, for grid growth and operation [9], it has gotten little attention in terms of other aspect. Grading up current electrical load has conventionally been used to forecast the hourly profile of local as well as national electricity consumption [10]. In comparison to today's circumstances, end-user freedom and more electrification will change things the hourly profile of load demand. Power-system planners must account for such changes in their modeling concepts and frameworks for analysis in order to propose cost-effective and practical solutions. Peak electricity demand is a big concern since it dictates the size and power producing capacity of the electrical infrastructure all times. Understanding how current and future developments, such as developing structures of integrated PV systems, heat pumps, electric vehicles, energy storage devices, variations in demand responses, and affect peak electrical load is critical. Long-term models including the power sector must incorporate better solutions to enable more accurate load forecasting by involvement of construction and transportation sectors.

2.2 Medium Term

Medium-term forecasting is useful for planning maintenance and obtaining fuel, as well as energy transaction and utility revenue review, and is normally for a week to a year. This information is useful for planning proper operation of power system, and has considerable advantages for businesses in the energy market, whether regulated or unregulated [11]. Taipower is a state-owned combined generation, distribution and transmission of power company which is an example of a regulated business that might benefit from the MTLF [12]. For many of these types of businesses, MTLF data can serve as a barometer of energy consumption and growth at the regional and national levels, as well as assisting with energy planning for the long and medium term [13]. Load projections over the medium term can also be utilized to plan and manage network repairs. The use of intermittent resources is maximized when fuel purchases for power generation are effectively negotiated. Major choices about long-term power system development, such as building of a power plant that takes two or more years to complete, typically necessitate longer-term estimates. Forecasting on basis of medium-term time, on the other hand, might provide useful information, viz, the improvement of the transmission grid for guiding the development of other infrastructure parts that must be completed in a shorter timeframe.

For distribution systems, grid congestion is a major issue, and it can have a considerable influence on consumer energy prices and efficiency of overall system [14]. In a regulated sector, MTLF can be utilized to increase overall system reliability by optimizing energy generation and transmission. In a regulated sector, MTLF can be utilized to increase overall system reliability by optimizing energy generation and transmission. Majority of the advantages realized in an energy market that is regulated through precise MTLF can be achieved as well as in a deregulated energy market. Transmission congestion is a problem that affects all energy delivery systems independent of legislation. Similarly, transmission and distribution companies are also affected in a deregulated energy economy. These deregulated enterprises can successfully use MTLF data to direct the upgrading their transmission network in order to provide better service to their clients.

2.3 Short Term

In recent decades, one of the most significant fields in the electrical industry is forecasting short-term load in order for electricity systems to run efficiently and reliably [15]. It is particularly important in the fields of load flow studies, planning and monitoring, power unit scheduling, and exigency analysis. This type of forecasting is generally last for an interval of one hour to one week. It is critical for a utility's day-to-day operations, along with proper scheduling regarding transmission of generated electricity. Another, type of forecasting, i.e., ultra or VSTLF (very short-term load forecasting) is used for controlling operation in real-time and varies between a few minutes and an hour in advance. Several forecasting methods and models have been created to calculate an accurate forecast for an hour to week interval. It is critical for a day-to-day operation of the utility to schedule power transmission and generation. Short-term load forecasting (STLF) has been a popular research area in recent decades. This STLF offers precise input into a previous day's scheduling, load power flow analysis, planning, and maintenance, exigency analysis, of power systems [16] to achieve improved reliability and effectiveness in power system operation, and to make it easier to reduce the cost of operation by offering standard statistical models, namely, ARIMA, ARMAX, SARIMA, exponential smoothing, multi-variable regression, and Kalman filter based methods. AI-based models such as knowledge-based expert systems, artificial neural networks (ANNs), evolutionary computation models, fuzzy theory and fuzzy inference system, and support vector regression also enhance the efficiency of the system.

To obtain a sufficiently precise forecasting level, many advanced hybrids using those AI-based models have lately been developed because of the rapid advancement of evolutionary algorithms (EAs) and novel computing ideas viz chaotic mapping functions, quantum cloud mapping process and computing concepts. By implementation of a superior methods, existing models such as ARIMA become capable of solving seasonal problems. STLF's study trends and progress have revealed a wealth of potential, deserving of additional investigation into this vital topic.

Considering these types of forecasting, several models of load forecasting have been developed and adapted for improvement in electricity generation and distribution.

3 Existing Models of Load Forecasting

The existing models for load forecasting are mainly developed on the basis of certain parameters which are realized as time series-based analysis [17] and estimates, qualitative techniques, and causal models. Generally, the models were compared in terms of the timeframe they are supposed to forecast. The most important issue becomes selecting the appropriate forecasting method depending on the qualities of the time series data. On the basis of different parameters, regression, bottom up, time series analysis, ANN, and SVM are the five most prevalent models being compared. Further, considering only the time series analysis, three different types of series models are constructed, as exponential smoothing model, moving average model, and ARIMA [18]. Many parameters under consideration hold a good inter relationship such as dependence on the frequency. Furthermore, the time series can be represented as a yearly annual budget or quarterly expenses, as well as monthly air traffic, weekly sales volume, daily weather conditions, hourly stock prices, minutes inbound calls in a call center, and even seconds wise web traffic. Furthermore, the time series can be represented as a yearly annual budget or quarterly expenses, as well as monthly air traffic, weekly sales volume, daily weather conditions, hourly stock prices, minutes inbound calls in a call center, and even seconds-wise web traffic. In consideration to so many parameters, three main types of time series models came into the market, namely, moving average, exponential smoothing, and ARIMA.

The ARIMA model focus on the way of forecasting, where prediction of future value is made on the basis of previous value are called univariate time series forecasting; while the predictions when made on basis of different factors other than series data, are known as multi-variate time series forecasting. Auto Regressive Integrated Moving Average (ARIMA) is a type of model that describes a time series using its own previous values [19]. These are the equation's own lags and lagged forecast mistakes, which will aid in forecasting values for future. Any 'non-seasonal' time series can be modeled using ARIMA models, that isn't random white noise but has pattern. If a time series has seasonal trends, the model is seasonal and is named as SARIMA, i.e., Seasonal ARIMA. The three terms that characterize an ARIMA model are p, d, and q, where p and q are the order of the AR term and MA term respectively, and d is the number of differencing steps required to stabilize the time series. However, the nonlinearity of the impacting components makes electricity load forecasting challenging, where ARIMA fails to address the problem.

In this regard, support vector machines (SVMs) have been used to address time series issues and nonlinear regression satisfactorily. The structural risk minimization (SRM) principle, which is better than ERM, is used in SVM [20]. Rather than minimizing the training error, an upper constrain on the generalization error is minimized, which is the most fundamental concept in SRM. SVM was able to achieve an optimal network structure using this technique. In addition, the SVM regression transforms the original data x nonlinearly into a space of higher dimension. This is analogous to solve a problem of linear constrained quadratic programming, guaranteeing that the SVM solution remains unique and optimal globally.

On the basis of the quantitative forecasting, those uses past data in numerical and continuous pattern form, many other load forecasting models have also been developed. Econometric modeling, judgmental forecasting modeling, time series modeling, and Delphi method modeling are among them. These methods create a forecasting logic by identifying the components that influence the forecast and constructing a functional form of the link between the identified factors. Short-term load prediction gives most suitable results using these models.

The load forecasting models require proper controlling techniques on the basis of criteria and parameters to be considered.

4 Controlling Method in Load Forecasting

Despite the fact that several techniques and models for forecasting have been created to compute reliable load forecasts, selecting an acceptable It is difficult to develop a forecasting model for a given energy network of varying demand pattern. This gave rise to many research questions relating to the responses of the criteria with that of the platform to conduct the forecasting algorithms. Keywords such as "electricity demand models," "electricity prediction models,", "electricity forecasting models," "online database," "advanced search tool," and so on are included.

Among the controlling methods, the search for causal linkages among various inducing factors and forecasted values is the focus of the cross sectional or multi-factor based forecasting approach, the time series-based forecasting methods, on the other hand, is more reliant on past data. When comparing these methodologies, the researchers discovered that time series forecasting is a lot easier and faster. This method avoids the numerous and subjective aspects that could sway the accuracy of a forecasting model while considering multivariable forecasting. Three types of time series-based forecasting models can be found [21, 22], namely,

- Models based on statistical data.
- Models based on machine learning.
- Models based on hybrid technology.

4.1 Classical Methods in Load Forecasting

In fundamental approaches, both qualitative and quantitative methodologies are used to anticipate outcomes, with the most appropriate kind being selected by the data available. The future load is estimated subjectively. Using expert opinions in subjective or qualitative forecasting methods, nonetheless, they are not simply guessing, but have developed organized procedures for creating effective forecasts without the use of historical data [23]. When historical data is inaccessible or scarce, such tactics are useful. These approaches include Delphi method, subjective curve fitting, and technical comparison method. Quantitative or objective forecasting methods, on the other hand, operates through mathematical and statistical formulas. With accessibility of data, these methods are implemented satisfying two criteria, viz, accessible historical data in the form of numbers, and it is acceptable to infer that few features of historical forms should persist in the future. Methods of quantitative forecasting include a diverse set of techniques, each with its own set of features, precisions, and prices to consider when selecting a method within a field for a given goal. Decomposition methods, regression analysis, Box-Jenkins methodology, and exponential smoothing, are examples of methods based on quantity [24]. The majority issues with quantitative prediction is either data collected over a period of time at regular intervals or data acquired at a specific point in time in cross section. However, the load forecasting methods can be summarized on the basis of the structural methods.

4.1.1 Statistical Models

A mathematical model is referred to as a statistical model that contains a collection of numerical assumptions about how sample data is generated. A model based on statistics can also be defined as highly idealized representation of the data-gathering process. Statistical model provides a mathematical relationship exists between non-random variables with one or more random variables. Several other statistical models for forecasting and prediction-making have also been developed based on specific criteria of optimal fit. Methods developed and implemented in this regard are Box-Jenkins basic models such as ARIMA, and ARIMAX, AR, MA, and ARMA [25], Algorithms for Kalman Filtering in State Space [26], Grey models [27] and exponential smoothing.

4.1.2 Autoregressive (AR) Model

Autoregressive models work on the principle that the series' most recent value. Y_t can be described as a linear mixture of prior loads. Mathematically, the auto regressive (AR) model can predict future load values. The value for a $\underline{p}$th order auto regression can be found through the expression shown below,

$$Y_{\mathrm{t}} - \sum_{i=1}^{p} y_{\mathrm{t}-1}\phi_i = \varepsilon_{\mathrm{t}} \tag{1}$$

where ε_{t} is the random noise, and ϕ_1, ϕ_2, ϕ_3, …, ϕ_{p} the AR coefficients that are unknown. The model's order specifies the number of lagged preceding values. As a result, the mentioned model can forecast future behavior on the basis of previous actions. This method considers the random noise along with the present and past values. Many industries, including finances, electrical load demand prediction, and digital signal processing units, have used autoregressive models for decades [28].

4.1.3 Model Based on Moving Average

The moving average-based model imitates the behavior of the process regarding moving average. It is just a regression model that reverts existing values linearly against one or more preceding values generate white noise. The time series is treated as unevenly weighted of a random shock series (ε_{t}) in a moving average model. Thus, the qth order of moving average based model can be represented as:

$$Y_{\mathrm{t}} = \varepsilon_{\mathrm{t}} - \sum_{i=1}^{p} \varepsilon_{\mathrm{t}-i}\theta_i \tag{2}$$

The noise series can be represented by model residuals or forecast errors once load observations are available. This gives rise to the technique a "duality," or invertibility, property. An infinite order or autoregressive form can be inverted or rebuilt, in this type of model which makes the difference between the MA with the AR processes. This is only possible if the MA parameters meet certain criteria, otherwise, the model will fail to meet the Box-Jenkins conditions for stationarity, invertibility, and stability [29].

4.1.4 Autoregressive Moving Average (ARMA) Model

George Box and Gwilym Jenkins created the autoregressive moving average in 1970. Because of their relative simplicity and effectiveness, ARMA models are becoming increasingly prevalent and have been extensively studied in load forecasting [30]. The present value Y_t is linearly stated in terms of the current value in ARMA models, prior values, and preceding noises. The ARMA (p, q) models are a combination of AR (p) and MA (q) autoregressive and moving average models, which can be mathematically expressed as below;

$$Y_{\mathrm{t}} + \sum_{i=1}^{p} y_{\mathrm{t}-i}\phi_i = \varepsilon_{\mathrm{t}} + \sum_{i=1}^{q} \varepsilon_{\mathrm{t}-i}\theta_i \tag{3}$$

4.1.5 Autoregressive Integrated Moving Average (ARIMA) Model

Because many time series, such as those connected to business and socioeconomics, have non-stationary behavior in practice, approaches that can deal with parameter and behavior fluctuations are required. As a result, the AR, MA, or ARMA models are unable to adequately characterize non-stationary time series because they can only deal with stationary data. As a result, Box and Jenkins presented the ARIMA models in 1976 with the goal of including non-stationarity as well. The parameters of autoregression (1, 2, …, p), the amount of distinctions d done to $(1 - B)$, with B as a lag operator, and the moving average parameters (1, …, q), and are the three types of parameters in the ARIMA Box–Jenkins models.

The lag polynomials are used to create the mathematical expression for the ARIMA (p, d, q) model, as illustrated below. The lag polynomials are used to create the mathematical expression for the ARIMA (p, d, q) model, as illustrated below in Eq. (4)

$$\phi(B).\nabla^{d}.y_{\mathrm{t}} = \theta(B).\varepsilon_{\mathrm{t}} \tag{4}$$

The seasonal model ARIMA (p, d, q) (P, D, Q)s, where s is the number of periods each season and P, D, and Q are the cyclical counterparts of p, d, and q, respectively. (SARIMA) models are seasonal versions of the ARIMA model. The autoregressive fractionally integrated moving average (ARFIMA) model is a useful generalization of ARIMA models that enables non-integer differencing parameters' values d. The ARFIMA has applications in time series modeling with a large memory. For electric load forecasting, the ARIMA models and their derivatives have had a lot of success [19].

4.1.6 ARMAX and ARIMAX Models

Apart from the random noise that disrupts the process, only time and load are required as input data for the ARMA and ARIMA models. Exogenous factors can occasionally be incorporated in the ARMAX and ARIMAX models because loads are influenced by the meteorological conditions and the time period of day [31].

In the model based on autoregressive moving average with exogenous inputs. In the time series the present value, y_t is linearly stated in terms of its preceding values. Present and historical noise levels, as well as current and previous exogenous variable levels (s), are all taken into account.

The ARMAX (p, q, r_1, …, r_k) can be expressed as,

$$\phi(B).y_t. = \theta(B).\varepsilon_t + \sum_{i=1}^{k} \Psi_0^i(B)v_t^i \tag{5}$$

where the i's represent the exogenous factor ordering (variables) $v_t{}^i$ and ψ^i (B) is an adequate coefficient polynomials

The ARIMAX model can be expressed in the same way as the ARMAX model, with the exception that the integrated part must be taken into account. This can be done with the help of differencing operator [32]. However, with many advantages, still the conventional methods fail to address all the issues and factors of an effective load forecasting. Because of the strong reliance on socioeconomic factors, long-term forecasting has a high level of uncertainty; As a result, a degree of error of up to 10% is allowed. Kalman Filtering algorithm can be used to reduce the inaccuracy of the mean squared model, thus considering the uncertainties.

4.1.7 Kalman Filtering Algorithm

Rudolph E. Kalman, who presented his important paper on a recursive solution to the discrete-data linear filtering challenge in 1960, is the name of the Kalman filter. The Kalman filter (KF) is a collection of state-space mathematics that can be used to estimate the state of an observable process in a computationally efficient (recursive) manner [33]. It can predict past, present, and future conditions, even if the nature of the system that is being represented is unknown. A Kalman filter can also be implemented to control noisy systems, such as electric power systems.

According to many researchers [34], the main rudiments that influence the electric load behavior are weather, random disturbances, economy, customer factors and time. In weather factor, wind speed, humidity, precipitation, and temperature, etc. are considered as adjustment in habit patterns in consumers like heaters, coolers, etc. The load curve impulses caused by the massive loads, such as steel mills or wind tunnels, are shut down or restarted, and considered as random disturbances. Other irregular events that are known in advance but have an unknown influence on the load are likewise classified as random disturbances. The type of facility, i.e., residential complex, commercial buildings, agricultural units, or industry), the size of the building, employees and electricity users are all factors to consider as customer factor. The time factors include the effect of loads during weekdays, weekends, holidays, and seasons.

The KF mechanism operates in two steps such as the corrector step (CP) and predictor step (PS). The PS, together with its covariance uncertainty, assesses the present load's state based on its previous state. After taking the new SMD measurement, a weighted average is used to update the predicted state vector. The estimate with the greatest degree of certainty gives greater weight.

The KF is usually expressed as a discrete-time linear dynamic system as state-space vector, shown below in Eq. (6)

$$x^t(k) = [x_1(k), x_2(k), x_3(k) \ldots x_n(k) \tag{6}$$

where k represents discrete time moment. Further, the smart meter device (SMD) readings can be realized as an observant vector $y(k)$. Finally the delayed estimator calculate the output as $y(k/k - 1)$ by the application of $(k - 1)$th output.

The Kalman filter has been commonly utilized for tracking in computer visuals that interact. It has been utilized for both prediction of motion and fusion of multi-sensors (inertial-acoustic). Furthermore, this filter is extremely effective in several additional areas:

Because the linear KF frequently fails to meet the strict requirement while detecting accuracy of forecasting in the presence of significant nonlinearities in the situation, numerous nonlinear versions have been created. To study the problem's hidden nonlinearities, the unscented Kalman filter (UKF) and extended Kalman filter (EKF) are occasionally utilized.

4.1.8 Gray System Theory (GST)

Deng was the first to introduce this approach in 1982. To predict the behavior of an unknown system, gray models simply require a small amount of data [35]. The GST's fundamental goal is to derive plausible governing laws for the observed system from available data, regardless of how complicated or chaotic it is. One of the most often utilized models is the gray model, which is capable of producing future primitive data point projections as well as coping with observed systems with partially unknown parameters.

The gray model's differential equation is crucial since it allows the power load to be forecasted. The system's n step forward predicted value can be found once the DE is solved. The GM (1, 1) is a model for forecasting time series with time-dependent changing coefficients and a differential equation (DE). It is feasible to moderate the system's uncertainty and hence lower its intensity. This is accomplished through the use of cumulative generation (AG). Because the models can employ random changes reflecting the quantity of gray, which is altered in a particular interval. These gray system theory-based models are commonly utilized in networks. The model that can be used to predict future load can be brought into market after it has been successfully tested for acceptable dependability, stability, and accuracy. All three forms of load forecasting can benefit from gray models. One of the main benefits of GMs is that they may be created without considering load distribution or load trend variations. However, their shortcoming is that they are only useful for effectively tackling problems with current exponential development tendencies.

4.1.9 Exponential Smoothing (ES)

The ES models are one of the most widely used statistical forecasting techniques, because to their precision, simplicity, durability, and inexpensive price [36]. They're also necessary for power system load predictions. The EF model's smoothing coefficients have a significant impact on the model's accuracy. This research also shows how to locate the smoothing coefficients having best values. Exponential smoothing is a practical forecasting method that uses an exponentially weighted average of previous observations to make a prediction. The present observation is given the highest weight, followed by the measurement preceding it, and so on. Single exponential smoothing (SES) based on Brown's approach, double exponential smoothing (DES) using Holt's method, and triple exponential smoothing (TES) are three forms of ESP. This exponential smoothening procedure further based on Holt-Winters method.

When there is no seasonal or periodic change in the data pattern, the SES model is used. It also does not have a trend in the earlier data. DES models, on the other hand, are frequently used in economics sectors which allow for anticipated values to have a trend. The TES model based on Holt-Winters concept can be computed in two different ways: additive and multiplicative. If the original data shows stable seasonal fluctuations, the additive type model is applied. When the original data exhibits large changes in seasonal fluctuations, however, multiplicative models are applied. The basic Holt-Winters method, according to empirical evidence, tends to yield over-or under-forecasts, especially for longer forecasting horizons.

Regression analysis, weighted iteration, and exponential smoothing as well as other enhanced algorithms like adaptive prediction and stochastic time series, have all been utilized for electric load forecasting.

Traditional statistical models have flaws and can sometimes cause unfavorable outcomes. This is because there are too many computational options, resulting in long times to solve and the difficulty of some nonlinear data patterns. As a result, machine learning and artificial intelligence techniques offer a viable and enticing option.

4.2 Modern Techniques in Load Forecasting

Forecasting and categorization are two applications where ANNs have proven to be useful. The use of artificial neural networks (ANNs) as a technique for anticipating electric load has been extensively studied in recent decades, and have garnered enormous popularity.

4.2.1 Artificial Neural Network (ANN)

In 1990, Warren McCulloch and Walter Pitts created the artificial neural network (ANN) approach as a time series forecasting substitute [38]. The ANNs try to spot patterns and regularities in the data and learn from their mistakes, and then deliver generalized results based on their previously acquired knowledge. Input, hidden, and output layers make up the most basic form of an artificial neural network model. The function of hidden layers, related weights, and outputs can all be considered when modifying the input values to the hidden node. An iterative training method is one in which the weights of the ANNs are changed over time. Some of the most widely used ANN algorithms for electric load forecasting include neural networks, feed-forward (FF), back-propagation (BP), radial basis function (RBF), NARX (nonlinear autoregressive with exogenous inputs), random neural networks, recurrent neural networks, and self-organizing competitive networks. In order to explore more better options, wavelet neural networks have also come up in load forecasting problems. For approximating arbitrary nonlinear functions using wavelet transform theory, WNNs are suggested as a substitute for feedforward neural networks.

4.2.2 Wavelet Neural Networks (WNNs)

Grossman and Morley introduced wavelet theory in the 1980s. Few scholars later proposed the wavelet neural network to make use of wavelet functions as well as the extensively used neural network (WNN). By computing the signal vector's internal product and wavelets base, a WNN may recognize pattern recognition-inspired feature abstraction of the signal using feature space. As a result, the network may efficiently learn the system's input and output properties without too much prior knowledge. WNN transmits the signal forward while propagating the error backward, resulting in a more accurate signal predictive value. For approximating nonlinear functions, WNNs have a rough capability and are robust.

Another form of controlling approaches in load forecasting field is extreme learning machine. Extreme learning machines are a subset of feed forward ANNs. Clustering, regression, feature learning, and sparse approximation are some of its applications.

4.2.3 The Extreme Learning Machines (ELM)

Extreme learning machines were introduced by Huang, Zhu, and Siew in 2004. They mainly deal with an FF neural network with a single hidden layer. Weights for buried layer nodes are chosen at random in the ELM, and the output weights of the ELM can be determined analytically using a least-squares solution. This means that, in addition to the weights that connect inputs to hidden nodes, the hidden nodes' parameters do not need to be changed. The nodes those who are hidden, on the other hand, can be assigned at random and never updated. ELM networks have a lot of potential, generalization performance that can learn thousands of times more quickly than backpropagation networks. Furthermore, the hidden nodes' output weights are frequently resolved in a single step, significantly reducing the time required for learning the algorithm. In both regression and classification difficulties, literature suggests that ELM models outclass support vector machines. For ELF forecasting, Chen [40] developed a unique recurrent ELM technique, while Rafie [39] employed a mechanism to improve the prediction by combining numerous ELM machines in a linear fashion and established the performance on three engineering challenges.

4.2.4 Support Vector Machines (SVMs)

Vapnik invented support vector machines (SVMs) as a reversion and organization approach in 1992. SVMs were first created to cope with pattern classification difficulties, but their use has now expanded to include regression techniques like support vector regression (SVR). The fundamental goal of SVMs is to create a unique decision rule with acceptable generalization ability by selecting a training data forming a subset which is known as support vectors. The training approach for an SVM model is similar to that of solving a quadratic programming problem with linear constraints. In contrast to the training of other networks, SVM solutions appear to be globally optimum and exclusive at all times. Instead of obtaining the least empirical errors the principle of minimizing the structural risk is taken into account while dealing with SVM models [41].

SVMs have gained in popularity over the last two decades, not just for pattern identification as well as regression analysis, forecasting, and dealing with prediction based on time series. However, the fundamental shortcoming of SVMs, is that they require a large number of computations, which dramatically increases the temporal complexity of the solutions.

4.2.5 Fuzzy Logic-Based Forecasting

Modeling and prediction have been prioritized in the field of electric load forecasting, with a focus on computational and artificial intelligence techniques, such as models based on fuzzy logic. Several researchers have used fuzzy logic models to forecast long-term load [42] and short-term ELF [43]. Furthermore, Jamaluddin et al. [44] used fuzzy logic to anticipate a very short-term peak load time, whereas authors [45] created a 220 kV transmission line short-term load forecasting model based on FL. Laouafi et al. [46] developed a daily load curve prediction system based on an adaptive neuro-fuzzy inference system, and Yao few researchers used an interval Type-2 FL system for short-term load forecasting.

Fuzzy approaches are extremely beneficial for dealing with uncertainties and are required for human specialists to acquire information. To produce good prediction outcomes, fuzzy theory is frequently integrated with other methodologies.

4.2.6 Genetic Algorithm

In the realm of electric load forecasting, GAs have been frequently used. Genetic algorithms have become one of the most widely utilized evolutionary computation approaches. GAs are a collection of genetics and natural selection principles-based optimization and exploration techniques. Nonlinear systems are frequently well-suited to these strategies. They carry out a specific optimization which is founded on the natural selection of the most effective solutions. The information comes from a variety of forecasting model having candidates' populations.

When the best appropriate forecasting model parameters must be discovered, this type of during selecting model, GA-based optimization is widely applied. The implementation of GAs was used to find the ARIMA model's best p, d, and q parameters [47]. Singh et al. [48] have used GAs to construct a load forecasting model based on neural network for ELF. For effective ELF forecasting, Semero et al. [49] applied the hybrid back-propagation-GA method. Khan et al. [50] described how Cartesian Genetic Programming developed Recurrent Neural Networks were used to forecast very short-term load. Furthermore, several additional works, such as [51], have also discuss and implemented GA-based ELF forecasting.

With increasing automation, the demand toward remote monitoring and controlling has increased to its peak. The knowledge of an expert must be easy to codify into software rules. This made the expert system as the most convenient and desirable option in forecasting load data apriori.

4.2.7 Expert Systems

Human experts employ rules and procedures to create expert systems. Experts must elucidate their decision-making process to programmers in particular [52]. According to researchers, a computer program that can explain, comprehend, and the knowledge base is expanded when new data becomes accessible, is called as expert system. It's a set of relationships between system load changes and changes in load-influencing external factors. In these processes, some rules do not alter over time, while others may need to be modified on a regular basis. Several studies on load forecasting have been conducted by developing various expert systems [40, 53, 54].

However, with many attractive features, the conventional hard computing and soft computing techniques leaves a scope for improvement in load forecasting. By integrating the best of statistical and machine learning methodologies, hybrid methods promise to improve time series forecasting.

5 Hybrid Method and a Classification System for Load Forecasting Models

Hybrid or combination models combine the benefits of multiple separate forecasting models. These methods can outperform single models in terms of prediction accuracy, and are thus widely employed in many forecasting domains. In this regard, a variety of forecasting methodologies, data processing techniques and optimization methods are available for constructing various hybrid models [55–57]. As a result, recent research has shifted its primary focus to the construction of successful hybrid models in the hopes of boosting prediction performance [58, 59]. However, there are no openly available guidelines on how to choose among alternative strategies when creating a hybrid model. In, consideration with many modern techniques implemented in various newly developed models, a case study of very short-term forecasting of load has been presented in next section of the chapter.

6 Case Study

A case study has been conducted as short-term forecasting of load considering the load data of the specific region. The specific region corresponds to Kolkata, located at 22.5726° N latitude, and 88.3639° E longitude. The single most important climatic component impacting load demand is commonly recognized as temperature.

6.1 Problem Formulation

The short-term load forecasting problem has been proposed in terms of the objective function mentioned below [60] in Eq. (7)

$$J_{\beta} = C_{t}^{+} \sum e_{t} + C_{t}^{-} \sum e_{t} \tag{7}$$

where, J_{β} is the total cost function, based on the load forecasting error, in consideration with hourly variation of temperature and humidity, e_t is the difference between the actual values and the forecasted values, defined as LF errors, $C_t{}^{+}$ and $C_t{}^{-}$ are the rates of electricity corresponding to positive error and negative error.

The load forecasting error is calculated [61] as given below in Eq. (8)

$$e_{t} = y_{t}^{EN} - f_{\beta}(x_{t} - l) \tag{8}$$

where $y_t{}^{EN}$ is the real value obtained at time t, as calculated following a well reputed Euclidean norm (EN), (x_{t-l}) is the independent variable at time $(t - l)$ for forecasting y_t, l is the lead time. The function f_{β} is based on an optimal parameter β.

Further, the actual data y_t^{EN} follows the Euclidean norm (EN) including weight factors and climatic factors of a specific place, while computing the forecasted value.

$$y_{\mathrm{t}}^{\mathrm{EN}} = \sqrt{W_1\left(\Delta T^2\right) + W_2\left(\Delta H^2\right) +} \tag{9}$$

$$\Delta T = T_{\mathrm{t}} - T_{\mathrm{p}} \tag{10}$$

$$\Delta H = H_{\mathrm{t}} - H_{\mathrm{p}} \tag{11}$$

where T_{t} and H_{t} are the forecasted temperature and humidity on hourly basis, and T_{p} and H_{p} are the past data for temperature and humidity on hourly basis. W_1 and W_2 are the weight factors.

6.2 Input Data

The study has been performed by considering the influence of climatic factors on the load data. The load data was collected data from a distribution center [62] of south Kolkata, India. Figures 1 and 2 represent the monthly load variation, with temperature and humidity, respectively.

The average temperature rises in March, April, and May, but the average load demand does not rise in proportion because to the large decline in average humidity. On the other hand, though the average temperature in the months of July, August and September does not rise much from that of the months from March to May, but as the humidity rises enormously, hence the demand for power increases. Electricity rates in Kolkata are defined as Rs 4.8/unit, Rs 5/unit, Rs 6/unit, Rs 7/unit, Rs 7/unit and

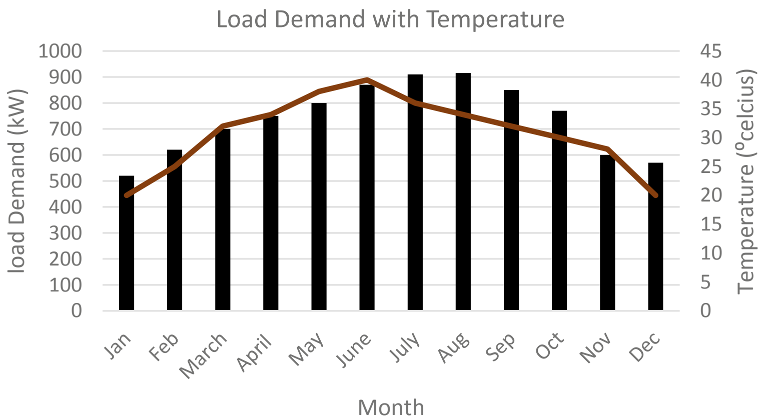

Fig. 1 Variation of average load demand versus temperature on monthly basis

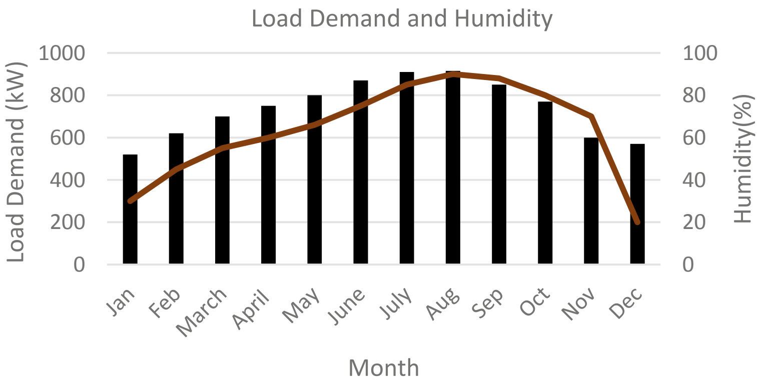

Fig. 2 Variation of average load demand versus humidity on monthly basis

Rs 9/unit for first 25 unit of consumption, for next 35 units, for further 40 units of consumption, for next 50 unit, for extra 150 units and above 300 units respectively. The C_t^+ and C_t^-, i.e., rates of electricity corresponding to positive error and negative error has been considered as Rs 6.41 per unit and Rs 7.33 per unit respectively, considering the average tariff of Kolkata.

6.3 *Result*

GOA was chosen to address this type of forecasting challenge because AI-based soft computing approaches are tolerant of imprecision and ambiguity, can generate and sense "linguistic variables," and are capable of deriving approximate solutions to problems. Furthermore, unlike other approaches, GOA is best suited to account for climate fluctuation in a specific location. The data pre-processing unit (DPPU), which identifies the problem and computes the desired outcome, is usually included in forecasting models. The grasshopper optimization method GOA was used in the present study as the control methodology.

6.3.1 Controlling Method and Implementation

The grasshopper optimization algorithm (GOA) is a relatively modern optimization method that was first developed in structural optimization issues by Saremi et al. [63]. The GOA imitates grasshopper swarming behavior, includes nymphs and adults; those are without wings and with wings respectively. Adults are used to investigate the entire search space and identify superior food source regions, whilst the nymphs are used to exploit a specific region or neighborhood of a certain place (exploitation). Exploitation and exploration are seamlessly balanced in this strategy, and it is theoretically included into a less sophisticated algorithm structure.

The current study, implemented GOA algorithm through following steps:

Step 1: A population of size N_{ij} is generated at first, where, the number of solutions is i, and j denotes number of hours; i.e., 24 h.

Step 2: The best position is found which corresponds to the best forecasted data, depending on the fitness function, as shown below in Eq. (12)

$$fit(e_{ij}) = \frac{1}{1 + f(e_{ij})} \tag{12}$$

Here, e_{ij} is the fitness function corresponds to the error of load forecasting, as mentioned in Eq. (12), which needs to be minimized.

The initial set of position is generated by the following equation,

$$y_{ij}^{\mathrm{EN}} = y_i^{\mathrm{EN}} * \mathrm{rand}(0, 1) - f_\beta\left(x_{i(\mathrm{rand}(0,1)} - l\right) \tag{13}$$

Step 3: GOA has a parameter called 'c' that varies depending on the number of iterations in order to strike a balance between exploration and exploitation.

This parameter 'c' can be calculated by,

$$c = c_{\max} - \mathrm{iter.}\frac{C_{\max} - C_{\min}}{M_1} \tag{14}$$

where M_1 is the maximum number of cycles.

Step 4: New set of position is calculated, which corresponds to new set of solution, through the equation mentioned below in (15) and (16)

$$y_{ij}^{\mathrm{EN}} = c\left\{\frac{c.\sum y_{i\max}^{\mathrm{EN}} - y_{i\min}^{\mathrm{EN}}}{2}.s(y_i^{\mathrm{EN}} - y_j^{\mathrm{EN}}) - \frac{\left(y_i^{\mathrm{EN}} - y_j^{\mathrm{EN}}\right)}{d_{ij}}\right\} + T_{\mathrm{d}} \tag{15}$$

$$s(r) = f.e^{\left(-\frac{r}{l}\right)} - e^{-r} \tag{16}$$

where T_{d} is the best-found solution, f is the intensity of attraction and the length of attraction is given as l.

Changes to c in Eq. (14) cause earlier iterations to focus on exploitation while later iterations focus on exploration. The algorithm's complete performance is improved by this balancing approach.

Step 5: The iterations are made, and the best solution from every iteration is being stored.

Step 6: The iteration count proceeds until it reaches the maximum cycle number, i.e. M_1.

Step 7: The cost function is calculated following Eq. (7), considering the best solution, i.e. minimum error function.

Table 1 Load Forecasting and Cost as evaluated by GOA

	Load forecasting error (e_t)	Total cost (J_β)		
	Positive Error	Negative error	Mean error	
Case 1	4.74	−0.07	2.405	Rs (4724 + 3921) = Rs 8645 per unit per month
Case 2	5.26	−0.04	2.61	Rs (3912.6 + 2814) = Rs 6726 per unit per month

Case 1 has been studied considering the summer months load demand, while Case 2 has been studied in consideration with winter months. As, the specific location is Kolkata, hence, in case 1 the humidity factor is quite low, while in case 2 the humidity factor in quite high.

Table 1 shows the load forecasting error and minimum cost for both case 1 and case 2 by implementation of GOA algorithm.

It has been noticed, that for case 1 the monthly cost achieved is about 22% more than that obtained during case 2. With less load demand in winter months, which depicts case 2, along with the computed monthly price the negative error obtained is also less than that attained in case 1. This signifies the consideration of region-specific climatic factors. Both the region-specific model as well as climatic variations are much needed in all types of load forecasting. The load deviation occurred on hourly basis resulted very less when computed by Grasshopper optimization method. Moreover, the proposed method is a single-stage based algorithm with several unique characteristics, such as all search agents participating in updating each search agent's position. This function aids load forecasting in meeting all regional climatic needs.

7 Conclusion

Many utilities have experienced a paradigm shift in how customers use power and how much they use as a result of the current recession. As a result, despite all of the mentioned studies discovered and carried by several researchers, the study door is still wide open for the use and adaptation of a variety of unique integrated models for energy and power prediction. In this regard, a case study has been performed using grasshopper optimization algorithm for a short-term forecast; which reflected a cost-effective scheduling for a region-specific load. Furthermore, special focus should have been paid to studying very short-term and mid-term load forecasting in order to fill the identified vacuum in the field.

However, the foundation for utility planning and a basic commercial concern in the utility industry has always been load forecasting.

The rapid growth of stored information in the demand forecasting, associated with data analysis provoked an utmost need for generating a powerful tool which must be capable of extracting hidden and vital knowledge of load forecasting from available vast data sets. It is critical for utilities to have accurate load forecasts, especially given the extraordinary risks that the electric utility industry faces due to a potentially significant change in the resource mix as a result of environmental regulation, aging infrastructure, projected low natural gas prices, and decreasing costs of renewable technologies. Moreover, the load forecasting is also required for rate cases, resource planning, financial planning, designing rate structures, and so forth. Forecasting load is not a one-dimensional procedure. Instead, utilities and politicians should be always looking for methods to improve the process, databases, and forecasting tools' state-of-the-art. A thorough load forecasting procedure includes complex data needs, dependable software packages, powerful statistical methodologies, and good documentation to build plausible narratives that describe customers' probable future energy use. Almost every state in every country has varied degrees of jurisdiction to promote database, forecasting tool, and forecasting process advancements. To establish procurement policies for construction capital energy forecasts, future fuel requirements are required. This data can only be available from an advance and accurate load forecast. Thus, a good forecast, reflecting the present and future trends of load demand, is the key to all planning. With many emerging models and control techniques, it is essential that utilities dedicate significant time and resources to developing reliable load projections.

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Deep Learning Techniques for Load Forecasting

Neeraj, Pankaj Gupta, and Anuradha Tomar

Abstract Electricity load dominates energy consumption and greenhouse gas emissions. There are increasing concerns about climate change and the need to minimize energy consumption and enhance energy performance. Energy management, optimization, and planning all depend on forecasting load energy consumption. The data-driven approaches are the most popular approaches to energy forecasting. Deep learning techniques are a new category of data-driven models that have emerged in the recent years. They offer improved capabilities in managing big data, attribute extraction characteristics, and a better ability to model nonlinear phenomena. This paper examines the effectiveness and potential of deep learning-based approaches for load energy forecasting. This paper begins with a literature survey, tracked through an outline of deep learning-based concepts, methodologies, and examples. Following that, the current trends in published research were examined and how deep learning-based approaches may be utilized for forecasting and feature extraction. The study finishes with an analysis of current problems and recommendations for further research.

Keywords Load forecasting · Deep learning · Data-driven approaches · Energy consumption

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1 Introduction

1.1 Motivation

In 2018, nearly one-third of global energy consumption was accounted for by buildings and construction, and almost 40% of global CO_2 emissions. These percentages will continue to rise in the coming years. It is critical to minimize energy consumption and enhance energy efficiency in buildings and facilities to maintain sustainability. Many strategies and approaches to energy planning, management, and optimization can forecast and predict energy loads. These applications include modeling predictive controls, load demand management, load demand response, and optimization. Short- and long-term forecastings are available for scheduled maintenance, renovations, and planning. Data-driven and physics-based models are the commonly used models for load forecasting. Nowadays, data-driven models are the most commonly used energy models. These representations can also be classified into either black-box or gray-box representations. But, the physics-based models can describe the system and its components in detail. However, such models require many measured parameters to be developed and calibrated. It can be challenging to obtain the parameters needed in many cases.

On the other hand, data-driven models usage mathematical models derived from measured data. These models do not require a large number of parameters nor detailed knowledge about the building/plant or system's internal components. Many buildings/plants have smart meters and automation systems, making data access easier. These data are easily accessible and can be used to forecast the load energy.

1.2 Compilation of Published Papers on Data-Driven Approaches for Load Forecasting

The popularity of data-driven approaches has increased in the recent years. There have been several literature reviews published. Each study focused on a different component of energy models. A summary will be provided in this section and highlight the main points of each paper. These selections are based on the most recent advances in artificial intelligence, especially deep learning-based techniques increasing in popularity from 2015 to 2016. The author in [1] compared artificial intelligence (AI) and statistical and physical models to estimate the energy consumption. The paper suggested future research directions, including developing better accuracy models, integrating these models into building energy management systems, and collecting data for future research. The capabilities and predictions of artificial neural networks were examined in [2, 3] looked at ANN, support vector machines (SVM), and hybrid models for the load forecast of energy usage. Ahmad et al. [4] have looked into how energy models interact with building controls and operations. The procedures are still not relevant, according to [5]. Future research should reduce the computing cost and memory requirements while retaining accuracy. Wang and Srinivasan [6] reviewed AI-based energy prediction. They are particularly interested in ensemble-based and single-point models. The author examined AI-based and traditional ways of predicting electricity [7, 8] examined time series-based forecasting strategies to estimating energy usage, highlighting popular approaches, and mixed methodologies. A full study of machine learning (ML) techniques for building energy prediction may be found in [9]. The authors suggested a few suggestions for future investigation. They a devised that deep learning algorithms be studied more because they are currently understudied. Furthermore, Ahmad et al. [10] have reviewed data-driven methods for the organization and estimation of building energy. The author has studied estimating, mapping benchmarking, and describing building energy models. And also focusing on how these methods have been used for large-scale and building applications [11]. The author studied data-driven models to forecast building energy consumption [12]. A breakdown of trends was also included.

Furthermore, Runge and Zmeureanu [13] provided a thorough study of artificial neural network applications for temperature prediction. The authors also recommended that further research should be done on deep learning-based approaches. It is engrossed on how ANN models can forecast power consumption [14]. In addition, the authors noted that future research should be focused on DL-based models. Aslam et al. [15] published a review of data-driven models for energy prediction. The focus was on feature engineering and data-driven algorithms. To the best of their knowledge, there has not been a literature review paper focused on DL models for forecasting energy consumption for energy loads. However, some published papers acclaim that forthcoming research on these techniques.

1.3 The Aim of the Literature Review

Although earlier literature reviews helped review and describe the current state using various applications of load forecasting models. This review aims to summarize the main points. There are still many gaps. The review paper [16] noted that there are not many review papers that emphasize new methods for load forecasting. It is noticed in a review paper that the deep learning models are the most emerging methods for load energy forecasting [17]. The author says no current paper focuses on load forecasting using deep learning approaches. Researchers may not be able to access the previous research because there are no review papers. The review paper [18] states that a future direction of research should be to establish a roadmap for machine learning-based load forecasting models. This paper attentions on establishing an idea for deep learning-based approaches that contribute to further research direction [19]. This paper reviews how deep learning-based approaches can predict load energy consumption. This paper addresses the gaps in papers identified by the literature analysis.

1.4 Objectives and Contributions

Deep learning approaches can be used to predict the load energy. The range of applications of such methods is extensive such as energy generation, smart grid networks, electricity price forecasting, and many others [20]. These models can also be used in other areas: air pollution [21], sales estimating [22], and others like health care and business. This work will only discuss the techniques used to forecast load energy consumption because of their wide range of applications. This literature review does not include integrating fuel cells, absorption, or adsorption systems. This paper will review several publications that use DL techniques to forecast load energy. This paper is organized as follows. The second section introduces deep learning and its many categories. The third section summarizes the current research trends. Section 4 examines the research that has employed deep learning-based feature extraction approaches in their research. Section 5 looks at papers that employed deep learning-based forecasting models. The future work, results and problems are discussed in Sect. 6. Section 7 brings the evaluation to a close.

2 Deep Learning Techniques

This part describes the fundamental descriptions, classifications, and approaches of deep learning that are used in exploration. Autoencoders, recurrent neural networks (RNNs), and deep neural networks (DNNs) are the most commonly used deep learning approaches. However, some approaches to deep learning, such as convolution neural networks (CNNs) and Boltzmann networks, are used in fewer cases. This section summarizes the most popular deep learning approaches that have been used for load forecasting.

2.1 History, Categorization, and a General Description

Deep learning approaches are popular for load forecasting due to their ability to deal with large amounts of data and feature extraction capabilities. So that the accuracy of the model is improved due to their features. This paper will overview several techniques and approaches to deep learning approaches. The word intelligence is the ability to process the information, take as input a bunch of information, and make some informed future decision or prediction. So, the field of artificial intelligence is simply the ability of computers to take as input: much information and use that information to inform some future situations or decision making. Deep learning is simply a subset of machine learning specifically focused on using neural networks, which extract useful features and patterns in the raw data and use them. Those patterns or features inform the learning tasks.

Traditional machine learning algorithms typically operate by defining a set of rules or features in the environment in the data right. The key idea of deep learning is that these features will be learned directly from the data itself in a hierarchical manner. These types of hierarchical features, and that is the goal of deep learning compared to machine learning, are the ability to learn and extract these features to perform machine learning on them. Today, we live in a world of big data, where we have more data than ever before. Neural networks are extremely and massively parallelizable. They can benefit tremendously and have benefited tremendously from modern advances in architecture that we have experienced over the past. Source toolboxes like TensorFlow can build and deploy these algorithms, and these models have become extremely streamlined.

The deep learning architectures have four to five levels of nonlinear operations. First, deep learning is a way for practitioners to discover good features. This requires some engineering skills and domain expertise. Deep learning approaches do not need domain expertise; they can learn automatically using the general learning process. This is the main advantage of deep learning. Feature extraction can also be done automated. Deep learning can also easily deal with huge amounts of a dataset to make precise predictions. Nowadays, precise prediction using giant data is a growing problem, but deep learning solves such problems. These models can store and hold more information than conventional ANNs. Deep learning methods have a few drawbacks. They are not easy to train the model and contain a lot of hyperparameters. There are three main ways deep learning-based approaches were used to build power estimation.

1. Increment the number of layers concealed in a feed-forward neural organization or multi-facet discernment framework.
2. A few repetitive neural organizations like RNN, LSTM, and GRU are utilized. These intermittent neural network models can have at least one secret layer. These models can be regarded as networks with intense structures.
3. Consecutively coupling various calculations into one in general construction.

2.2 Autoencoder

In the case of autoencoder, the neural networks consist of multiple hidden layers. An autoencoder is composed of two sections. One is an encoder, and the other is a decoder section. An autoencoder's goal is to be able to recognize the dataset and reconstruct it using training. The encoder is the input of a hidden model, and the decoder is the output of a hidden model. Input data is represented by y, which is s equal to (y). To make the output, the decoder extracts the hidden representation. The training aims to reduce the difference between input and output so that y equals to y'. Generally, an autoencoder is used for feature extraction in huge datasets. The structure of the autoencoder is shown in Fig. 1.

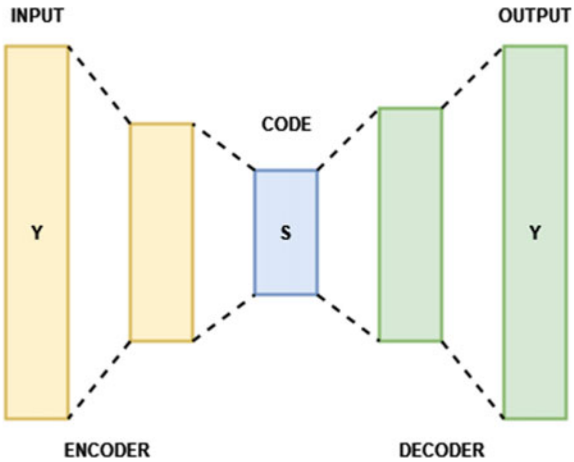

Fig. 1 Autoencoder

2.3 *Recurrent Neural Network*

Deep learning models can be used to process time-series data. Time-series data is a series of data tracked over time. Recurrent neural networks can solve the problem of feed-forward networks. The feed-forward networks such as density connected networks or convolutional neural networks. In other words, feed-forward networks do not consider the relationship between the current sample and the previous samples. The relationship between current and previous data is significant for some kinds of data, especially time-series data. The previous data predicts the following data to solve this problem. A loop is purposed to memorize the previous information [23]. RNN has a loop current connection/recurrent connection, representing the output back to itself. The RNN has a memory to remember the previous output and when the following input comes. RNN calculates a new output based on the current and previous outputs. So, recurrent neural networks can remember and memorize the previous data in the previous state. Therefore, the temporal relationship is considered to understand better how it works and can unfold on a loop in the time domain. Figure 2 shows that the input is time-series data x, and the output is data h. So first, the input data is unfolded data in the time domain. The data from the beginning of x_0, x_1, x_2 to x_t will have the output h_0, h_1, h_2. It has only one cell, but this is the same cell at a different time. So, RNN will consider the previous input x_0, save the output step, and then pass it to the next state. So when it has the following data x_1, it can use x_1 and the previous output to calculate new output h_1. Then set the state and then paste the state to the next cell. So this Fig. 2 unfolds an unknown loop that can better illustrate how RNN works.

$$S_t = F_w(S_{t-1}, X_t) \tag{1}$$

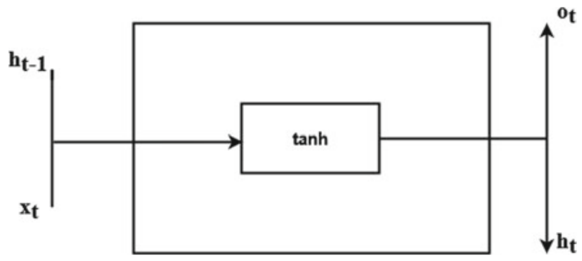

Fig. 2 RNN

This equation explains what RNNs are and how they work. X_t denotes the input at time step t, S_t denotes the state at time step t, and F_w is the recursive function.

$$S_t = \tanh(W_s S_{t-1} + W_x X_t) \tag{2}$$

A tanh function is a recursive function. W_x multiplies with the input state, while W_s multiplies with the prior state. Then, it passes through a tanh activation to get the new state. The weights are W_x and W_s. The new state S_t is multiplied with W_y to produce the output vector. It can be seen in Fig. 2, the input and output states are calculated using the previous and new state [24].

2.4 *Long Short-Term Memory (LSTM)*

RNN suffered a diminished and exploding gradient problem. The researcher proposed a long short-term memory model to solve the gradient management and exploding problem. It has become very successful. The long short-term memory adds multiple gates. First, they add an input gate to control if the new input is in or ignore the input and then add the forget gate. So, it can delete the trivial information. The output gate can decide to let the info impact the output at the current time step. The input gate usually outputs from zero to one. So if the output is zero, then the input will be ignored. If the gate output is one, the input will pass through to the hidden cell. So the gate is like a switch, and it is output continuously from zero to one. So it can control the part of the input that is passed to the hidden cell. So another gate is the forget gate, or if the forget gate is zero, the hidden cell's memory will clean right to zero. The last one is the output gate or the controller output that decides if the information pass to the next stage or not. The original LSTM picture is not easy to understand. The LSTM model has two paths. One is to update the memory state in the model. Another one is like the original RNN to pass the output to the next stage. For LSTM, it has two paths to pass the data to the next stage. The forget gate can control if it ignores the information. The sigma means the sigmoid activation function. The output of the sigmoid is between zero and one. So the sigmoid activation function is used as a switch of zero means turn off, and the one is turned on. It is also assigned a value between zero. The activation is multiplied by the output with the previous state to control the portion of the information. The second state is the input gate. It can control to pass how much input information passes into the state to generate the new form. The third gate is the output gate that can control how much information is to pass to the next stage. LSTM model helps to solve the vanishing gradients problems [25].

$$i^t = \sigma(W^i[h^{t-1}, x^t] + b^i) \tag{3}$$

$$f^t = \sigma(W^f[h^{t-1}, x^t] + b^f) \tag{4}$$

$$o^t = \sigma(W^o[h^{t-1}, x^t] + b^o) \tag{5}$$

$$\overline{C}^t = \tanh(W^c[h^{t-1}, x^t] + b^c) \tag{6}$$

$$C^t = f^t C^{t-1} + i^t \overline{C}^t \tag{7}$$

$$h^t = \tanh(C^t) * o^t \tag{8}$$

i^t, f^t, and o^t are the input, forget, and output gates of the LSTM cell. W represents the recurring construction between the previously hidden and the existing layers. The hidden layers are connected to the input through the weight matrix. The cell state $\overline{C}$ is calculated and depending on the current and previous input. C stands for the unit's internal memory. Figure 3 shows the equations that describe the behavior of all gates in the LSTM cell. As inputs, each gate accepts the hidden state and the current input x. The vectors are concatenated, and a sigmoid is applied. $\overline{C}$ is a new potential value for the cell's state. The input gate controls the memory cell's updating. As a result, it is applied to the $\overline{C}$ vector, which is the only one that can change the state of the cell. The forget gate determines how much of the previous state should be remembered. To get the hidden vector, this state is applied to the output gate [26] (Fig. 4).

2.5 Convolutional Neural Networks

Convolutional neural networks are a family of neural networks characterized by convolutional layers. They are particularly suitable for tasks involving data with spatial dependencies, such as images and videos. Convolution is a filtering operation applied to the data to detect certain features. This is just a matrix of numbers for a computer, with one value for each pixel. For seeing the borders, take a smaller filter matrix called kernel and perform an element-wise product between the kernel values and a portion of the image. Then sum up the results and get a single value, which indicates whether in that portion of the image borders are present or not. The kernel is then shifted by several pixels to cover another section until the whole image has been covered. The final result is a new matrix, called a feature map, whose numbers describe the borders. A convolutional layer implements several kernels,

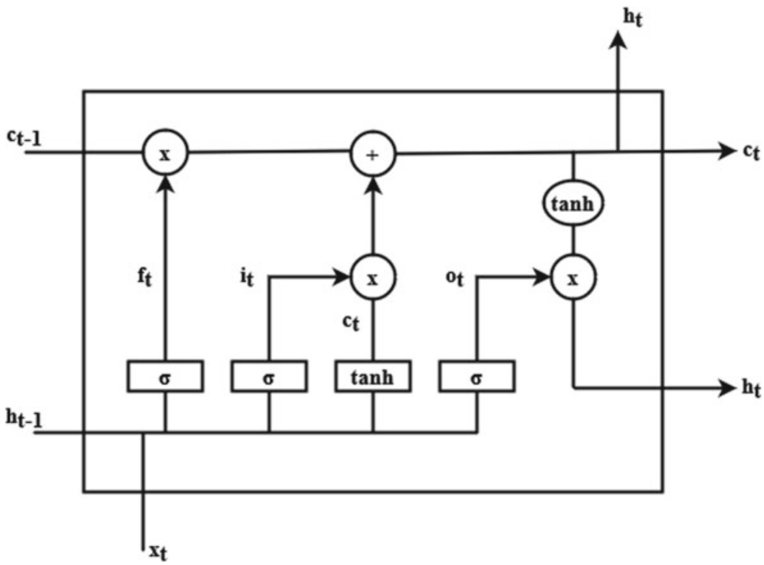

Fig. 3 LSTM

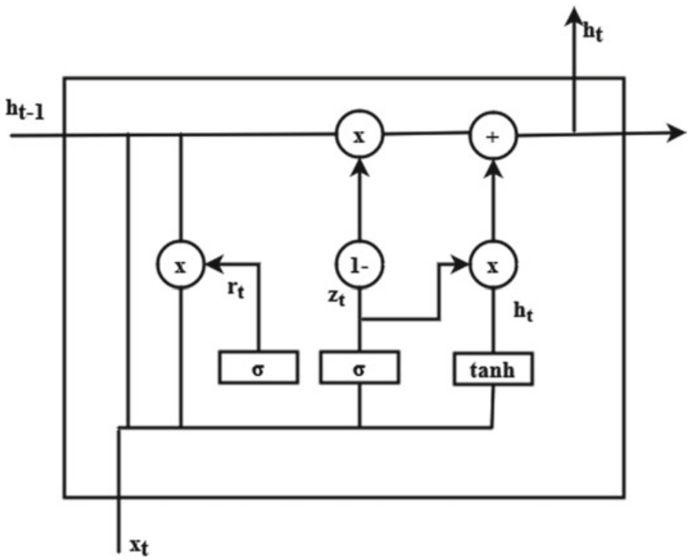

Fig. 4 GRU

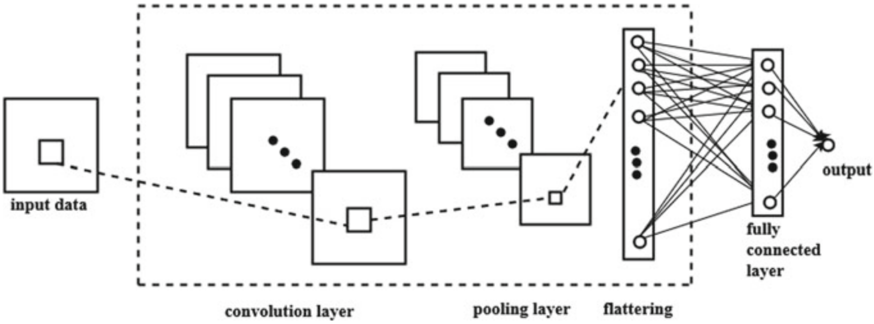

Fig. 5 CNN

each detecting a specific feature. The cool thing about convolutional layers within a neural network is that it does not have to design the kernels in advance.

During training, the network decides the important features and adapts the kernel to detect them. The parameters to set in this stage are the number of kernels to train, the kernel size, and the convolution dimension such as 1D, 2D, and 3D convolution. The difference between 1D, 2D, and 3D convolutions is: the convolution dimension sets the number of axes on which the kernel moves. In a 1D convolution, the kernel moves along one axis; in a 2D convolution along two axes, and so on. Convolutions with different dimensions discover features in those dimensions. The data dimension does not necessarily bind the dimension of the applied convolution. For example, black and white images are 2D objects, while color images are 3D objects because of the additional color channel. In both cases, if we are interested in 2D features, like borders, a 2D convolution moving along the width and height of the image will do the job. The same holds for time series. There are two dimensions, values and time. If we want to discover a 1D feature such as upward trends, we can apply a 1D convolution. Therefore, the dimension of the convolution is determined by the dimension of the feature to discover, not by the object's dimension. A CNN is represented in Fig. 5. Allude to reference [27] for a point by point depiction of a CNN's overseeing conditions and merits.

2.6 Deep Belief Networks

Deep belief networks (DBNs) is a type of deep neural network created from [28]. DBNs can be described as a range of algorithms that combine probabilities with unsupervised learning to produce outputs. The restricted Boltzmann machines (RBM) are fundamental to the DBN. It can then be configured to exhibit desirable properties [29]. The visible layer or input layer is the first layer of RBM. The hidden layer is the second. The RBM is illustrated in Fig. 6.

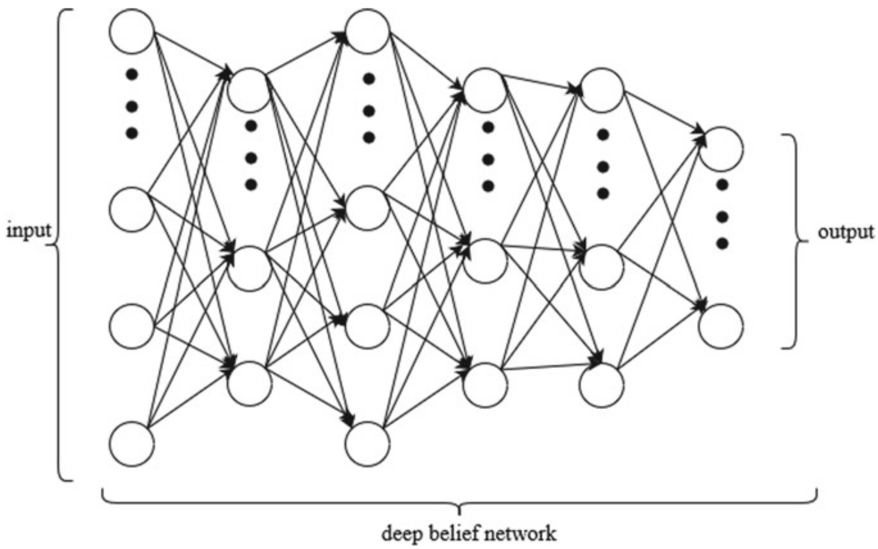

Fig. 6 DBN

Figure 6 shows an example of a DBN. Although stacking multiple RBMs together can produce large models, it may prove cumbersome to train such large models. Refer to references [30] for more information about the governing equations, merits, and limitations of RBMs, DBNs, and their potential benefits.

2.7 Deep Feed-forward Neural Networks

Deep feed-forward neural networks (DFFNNs) are another popular technique for forecasting energy in buildings. These models differ from the standard feed-forward neural networks (FFNNs) because they have multiple hidden layers. To extract more information from the data, additional layers are added. Research has shown that there are many other deep learning-based structures [31] (Fig. 7).

3 Trends in the Present

From 2000 to 2021, the publications are looked. This section examines the trends that have been observed in the published data.

3.1 Level of Building Application

Data-driven models need to be validated on testbeds before being used in real-world applications. There are four levels to these testbeds. The forecasting model may be modified by the building level data and time steps data. According to the analysis, the studies were broken into four categories: district level, buildings, sub-meter level, and component level. The use of data from existing systems for large-scale installations and district heating/cooling systems may explain the tendency to focus on whole building cases and districts.

3.2 Qualities of Data

In each case study, the data size varies to the length and amount of data. DL-based approaches are being suggested to solve the problem related to large amounts of data to handle the big data. According to the observed breakdown of published work, 18% used less than six months, 23% used 6 months to 1 year, 57% used more than 1 year, and 2% did not justify their data size. This review also examined data types. Three types of data are commonly used in the published research papers: energy plus, real data, and target data. According to the findings, 93% of the case studies were applied to real data. Following that were 4% for experimental data and 3% for the target data.

3.3 Output Variables

The DL-based model's energy usage was applied to the forecast. The sub-meter and components are target variables like electric heating and cooling demand, etc.

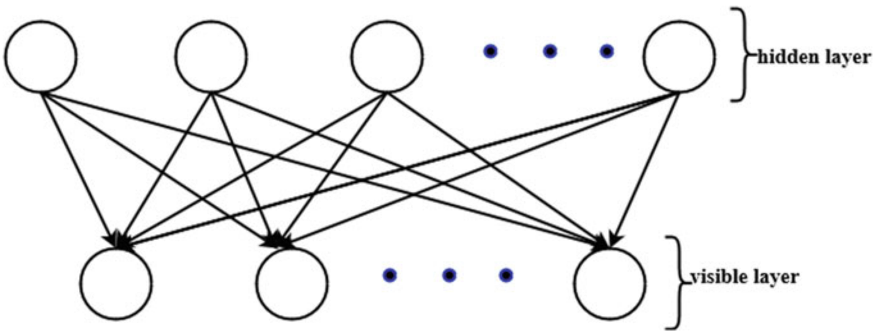

Fig. 7 Deep feed-forward neural network

3.4 *Input Styles*

The characteristics or regressors utilized as inputs into the forecasting model are inputs. All energy-based models require that you choose the correct input data. Data-driven models require the selection of appropriate input data. The poor choice of input variables may cause poor forecasting performance. The most commonly used features were: environmental data, such as outdoor temperature, and historical data, such as past energy use. Nowadays, it is not easy to find out which attributes are the most crucial. These may depend upon the various case study conditions such as weather, place, and type of structure. So, many feature extraction techniques were introduced in published research. Although a thorough examination of feature selection may be beneficial, the focus of this paper will be on DL-based approaches for variable selection.

3.5 *Granularity of Time*

Forecasting models have two main types: forecast horizon and resolution. The forecast horizon is the projected time. The term "resolution" mainly relates to the data's time step. These two temporal granularities are applicable in various ways to forecast models. For hourly time step data, a forecast horizon can be used to estimate a horizon of 24 h ahead. The models' resolutions were 1% annually, 0% monthly, and 3% weekly. There are three types of prediction horizons: medium, long-term, and short-term [31]. It is important to note that the classifications mentioned above are not set in stone and may differ from those published.

4 Feature Extraction Applications Using Deep Learning

Feature selection is a process that reduces the size of an initial dataset into more manageable segments. Big datasets take a lot of computational time to process the model. So, computational time can be reduced by choosing the appropriate attribute. This can improve accuracy, reduce overfitting risks, and reduce computational resources for forecasting-based models. Recently, DL-based approaches are widely used for feature extractions and load forecasting. Due to its fast computing speed and simplicity of construction, this model has grown in popularity. Many studies have compared their efficacy to that of other data-driven models. In [32], compared four feature extraction techniques and forecasting models. This paper examined four different feature extraction methods:

(i) Technical, which selected the model on the basis of technical expertise.
(ii) Analytical calculated actual data from a response variable that could be used as a criterion.

(iii) Architectural, in which the time series was transformed.
(iv) Autoencoder.

Variables were selected from various models to forecast the energy load with different time horizons. Although, DL-based models are the best estimating performance models, the researchers conclude. The DL-based model is compared with data-driven models such as autoencoder and machine learning approaches in [33]. In the case of a retail facility, these models were utilized to forecast the total energy use. The model was used with a horizon of 60 min and 30-mintime intervals. The autoencoder and machine learning approaches provide lower estimating errors. In [34], compared different feature selection methods. The performance of each method was compared with feed-forward neural network (FFNN), support vector regression (SVR), and random forest models. The models have trained with the resolution of 15 min and ahead horizon. The observation showed that the prediction error was reduced in 33% of the AE coupling clusters. However, the predicting inaccuracy was either maintained or significantly increased in 1/3 of the clusterings. In [35], the autoencoder model is compared with support vector machine (SVM) and FFNN. In this paper, forecasting was conducted on the office building energy load with the resolution of 5 min. They targeted the heating load and cooling load. Chitalia et al. [36] compared the various data-driven models for estimating the energy load of a commercial building with the resolution of 24 h ahead. This research found that combining DL feature extraction with estimating models results in a high-performing estimating model. DL feature removal methods to anticipate building energy use are still being developed. More study is required to compare these models across different case studies and applications.

5 Application Summary at the Load Level

To predict, the energy loads of the whole plant are the plant-level applications. The published research is classified into the following categories: educational, industrial, domestic, combined, etc. Combined states to publications that have applied their findings to various case studies involving various plant kinds.

This section contains publications that employed a DL-based approach to conduct a study on power loads. According to the analysis, all of the paper in this area came from educational places. There were also several case studies involving educational structures. Within this research, there are many case studies discussed. Cooling and electricity usages are the essential target load in the used research. There are still several gaps in understanding DL forecasting models for educational buildings, such as heating and lighting. This discrepancy might be due to the difficulties in obtaining data for specific loads [37]. On the other hand, the energy loads of heating and lighting can account for a significant portion of an industrial or educational building. They use 30% for heating and 15% for lighting [38]. As a result, future work may benefit from looking into these possibilities. In some papers, cooling loads were examined by

DL-based predicting models [39, 40]. Increasing the predicting efficiency for cooling loads uses an autoencoder for variable extractions [35, 45]. The author discussed in [28] the performance of the RNN, LSTM, and GRU-based models to predict the cooling loads using various approaches such as direct and recursive approaches. This paper showed that for the RNN model, the direct approach was more reliable. In [40], twelve predicting models are compared for the cooling load applications. According to this paper, the LSTM model gives more accurate results. In [41], various university campus heating load was predicted using the RNN model. According to their work, the RNN models worked better than the other machine learning-based approaches for medium and long-term estimation. They show that to get better results to predict the thermal energy loads, RNN models are used. More study is needed to corroborate the previous work based on different case studies. Marino et al. [42] show how GRU-based models may be used to predict energy usage. After examining several strategies for inferring missing data, GRU forecasting models were tested. For LSTM models that output power load predictions in educational buildings, see references [31]. The authors of the reference publication [43] evaluate the efficacy of several deep learning models.

6 Results and Discussion

Because deep learning approaches and techniques can manage vast volumes of data and give superior results, they have seen rapid expansion in the recent years. There is substantial research on their application in load energy forecasting. According to the observations, most of the DL-based models are used to predict the full power loads. They also target the energy loads for the entire plant. Most DL techniques have been used in the LSTM and deep feed-forward neural networks. When comparing forecasting performance with other ML-based methods, it was found that DL-based methods typically lead to better performance than ML-based ones. In some cases, however, it did not. Similar observations were also observed when the models were used as forecasting models. Despite the strong outcomes, there are still considerable hurdles to be overcome.

6.1 Challenges

Although the use of DL-based methods is still in their initial stages for forecasting the energy loads, several new and thrilling tasks remain. The most significant challenges that have been observed are divided into two categories:

1. The difficulties that the research community is confronted
2. The DL-based methods are faced the technical challenges

The following are the main challenges which the researchers face:

1. Most papers used unpublished proprietary datasets. This point was raised in a review study on data-driven models [38, 44]. Because of the extensive usage of proprietary data, it is not easy to produce the results, conduct comparison, and expand on the work of others.
2. As a result of the developing number of publishers, there is no standard for foreseeing model data in each diary composition.
3. Inadequate descriptions of the components/or methods used in their research. It was found that some papers did not specify their forecast horizons or hyperparameter tuning approach.
4. Many performance metrics can be applied to each publication. The most common performance metric in research is the mean absolute percentage error, found in references [45]. However, it is not always employed in the study. Occasionally, the author will utilize other metrics or change the measurements.
5. The issue is further complicated by using unclear terms in research.

A few significant challenges have been identified in the research on DL-based models. It is challenging to develop and test DL-based models without guidelines. Creating, applying, and comparing such models are much more challenging because there are no guidelines. According to the findings, the majority of articles had changed their hyperparameters by trial and error. Building various models and ensuring repeatability may be easier with an automated method and guideline. The models can improve forecasting performance at multiple levels, but they have a trade-off: increased complexity of the model and longer training times than typical machine learning approaches. Future researchers would benefit from the establishment of guidelines for DL modeling. This will provide them with a standard set of criteria that they can use to compare and build on models. This could allow for more generalizations more quickly.

6.2 Data Collection and Results

6.2.1 Data Collection

Data is collected from the Delhi power plant from January 2011 to December 2020 with hourly resolution. Before processing, any analysis dataset is normalized using a min-max scalar. Figure 8 represents the power consumption data before normalization, and Fig. 9 represents the data after normalization using a min-max scaler. Normalized data provides equal weights to each attribute. Because they are more significant numbers, no one attribute influences model performance in one way.

6.2.2 Results

From Figs. 10, 11, 12, it can be observed that the forecasted load performance is identical to the actual load consumption. All deep learning models provide accurate

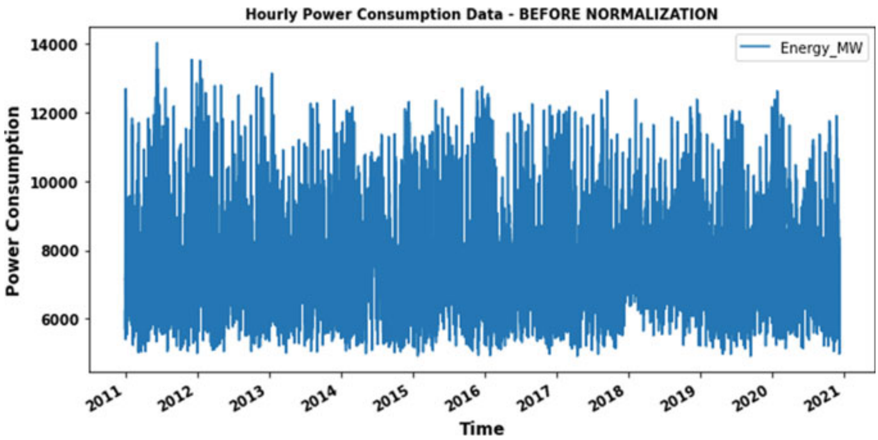

Fig. 8 Hourly power consumption data–before normalization

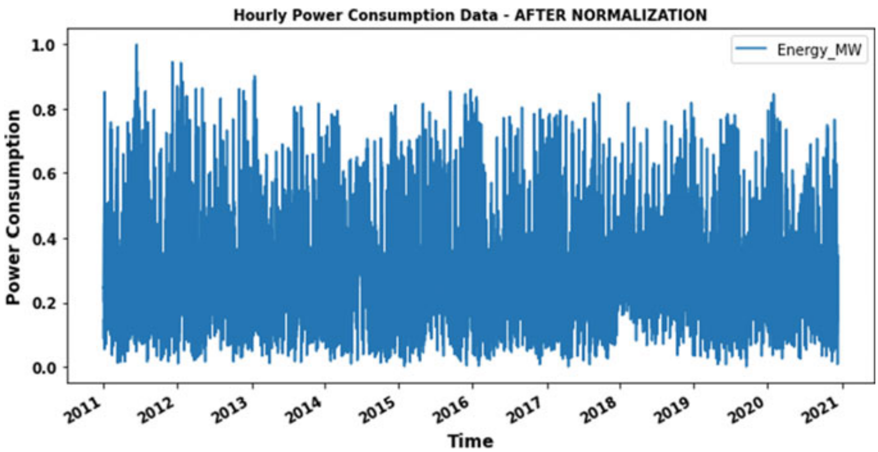

Fig. 9 Hourly power consumption data–after normalization

results as compared to the actual values. It can be seen that where the behavior of the power consumption load is unstable. The predicted results are that diverging from the actual values is moderately important. However, the power load consumption curves are repeated in all cases, as shown in Fig. 13. If the power load consumption graph is irregular or stable, the forecasted values fluctuate, especially when the power consumption load appears irregular.

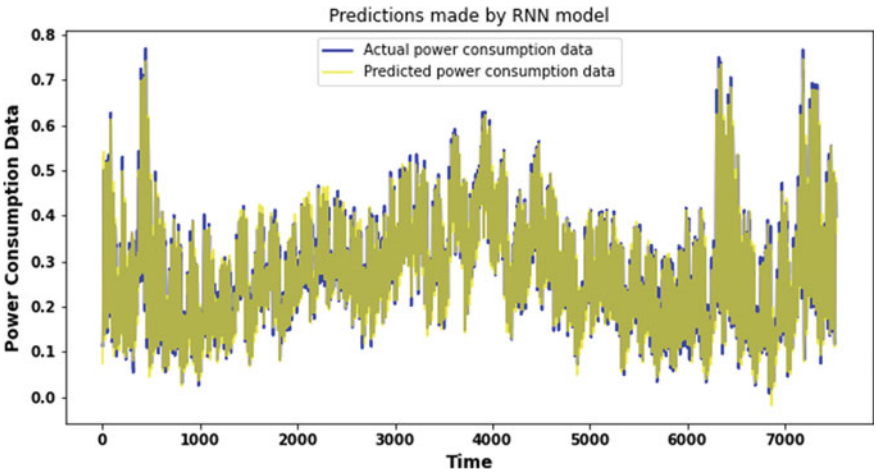

Fig. 10 Prediction made by RNN model

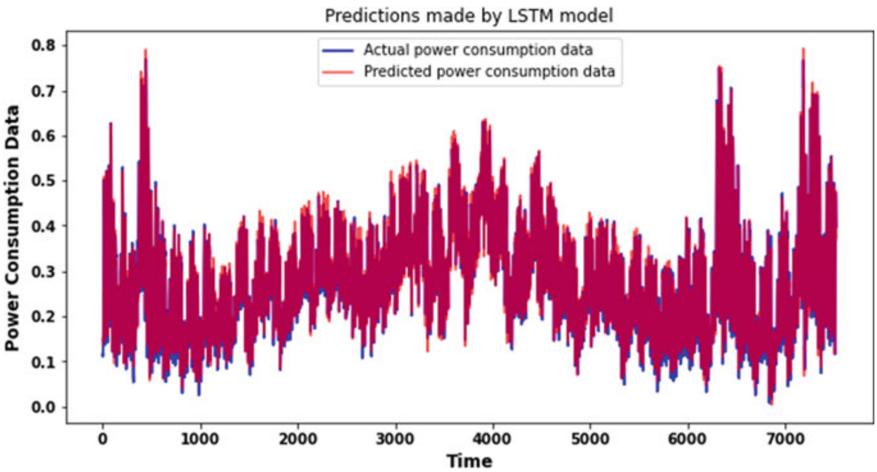

Fig. 11 Prediction made by LSTM model

6.3 Future Research Prospects

The potential of coming ways for DL-based methods in energy load forecasting contains:

1. The improvement of DL approaches across a scope of area types for load forecasting focuses on comparison-based papers.
2. The applications of DL models in research papers have not been much discussed.
3. Different case studies have been analyzed using DL gray-box models.

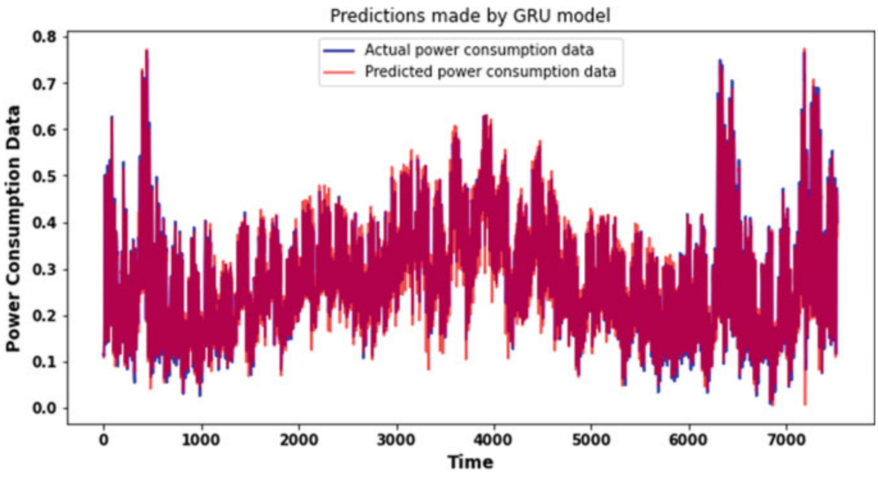

Fig. 12 Prediction made by GRU model

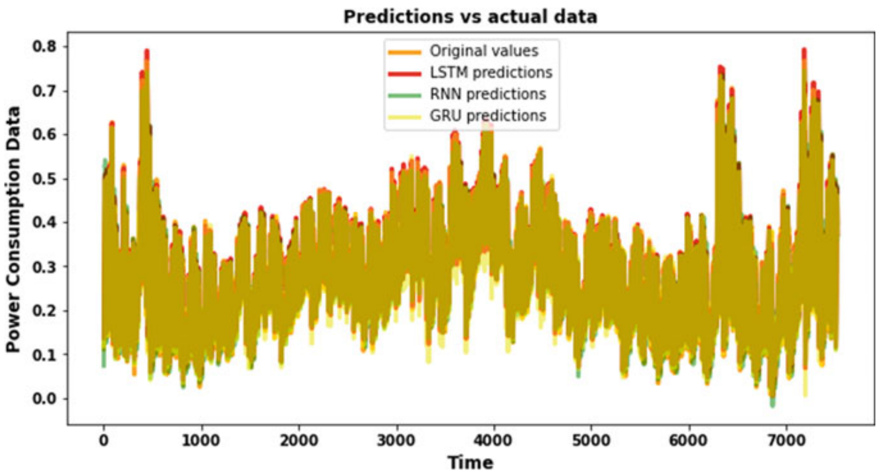

Fig. 13 Predicted versus actual

4. Analyze the sensitivity of DL models and their uncertainty.
5. The selection of hyperparameters for the DL model proposal establishes the guidelines.
6. The production of mountable DL-based models can be immediately evolved and tuned for use in various areas for load estimation.
7. The growth of strong models can provide accurate predictions even in the case of sensor fiascos, variations of the process, and other unforeseen events.

8. Implementation of innovative deep learning-based approaches in real-world applications, such as predictive model controllers, and demand-side management scheduling optimization.

7 Conclusion

This paper reviewed deep learning approaches that can be used to estimate the load energy consumption. Firstly, the concept and characteristics of deep learning approaches were discussed. After that, most widely used and vital methods of deep learning were presented. The basic overview and types for deep learning-based models are provided first, followed by an overview of some of the most popular methodologies. Following that, this report included a summary of current trends based on published studies. After that, attributes extraction and load forecasting using deep learning techniques were studied. At last, this paper discusses some issues related to such type of model using deep learning approaches. According to our review, deep learning strategies have proved to generate more significant performance outcomes when used to feature extraction when compared to other methods, according to our consideration. Furthermore, comparable effects were reported when the deep learning approaches were used as prediction models. Because there are few comparison-based studies among DL-based approaches, determining which one produced the most promising outcomes is challenging. However, the current results are encouraging, and future research should build on the existing part of the information. Despite the significant growth of the papers and case studies in the recent years, there are still several obstacles and tasks to be completed. The applications of the deep learning approaches are not typically used for case studies and target attributes. But the comparison of the deep learning approaches across various case studies and implementation of DL-based models is the actual application of such works. Many applications for energy management and improvement rely heavily on forecasting models. Predictive control, demand response management, fault detection, and optimization models are examples of such applications. The conversation and discoveries of this paper might assist the researchers with concluding which profound learning-based models are utilized for load determining.

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