International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 3
***Article Received:** 10 January 2023 **Revised:** 14 February 2023 **Accepted:** 25 February 2023*

Utilization Of Artificial Intelligence (AI) And Machine Learning (ML) in the Field of Energy Research

Dr. Mohammed Saleh Al Ansari

Associate Professor

College of Engineering, Department of Chemical Engineering

University of Bahrain

Malansari@uob.edu.bh

Abstract

Many governments have committed to becoming carbon neutral by 2050. The main argument is that renewable resources are more eco-friendly than fossil fuels. However, the unpredictable nature of solar and wind power results in either excess or lack of energy generation. This article will evaluate the current machine-learning-based solutions for forecasting renewable energy demand and capacity. Many researchers have used machine learning (ML) to anticipate the amount of generated wind or solar energy. SVM, RNN, NN, and ELM are the most utilized algorithms. Prediction accuracy is improved through optimization (metaheuristics and evolution). These methods can forecast renewable energy for periods ranging from seconds to months. This article compares several ML methodologies and metaheuristic strategies and reviews the current state of research. The hybrid MLS outperforms the standalone optimizers. A more extensive data set for ANN, the introduction of NWP, and a shorter prediction timeframe are suggested as alternatives to Bayesian and random grid tuning. Further research on probabilistic predictions and mathematical relationships between inputs and outputs is needed to close the research gap.

Keywords: Renewable energy; Machine learning; Energy forecasting; Metaheuristics; literature review, Recycled aggregate concrete, Durability

Introduction

Solar and wind power are the two forms of renewable energy that are now the most common and have the most potential. These are renewable forms of natural energy. The application of their use is beneficial to people without being detrimental to the environment. Solar energy, in both its direct (heat) and indirect (photovoltaic) forms, is the most environmentally friendly form of energy (Arevalo, Santos, Rivera, & conversion, 2019). Electricity can also be produced through the use of wind's kinetic energy (Shoaib, Siddiqui, Rehman, Khan, & Alhems, 2019). Because both sources are affected by the weather, it is hard to predict their expected patterns, which results in the requirement for grid maintenance. Solar and wind energy are susceptible to interference from a variety of factors, including air pressure, temperature, humidity, wind speed and direction, insulation time, and many more. As a result, photovoltaic (PV) power is an important component of most renewable energy sources. As a result, a large number of researchers have been interested in its modeling and its prediction in order to improve the control of the electric structures that are composed of PV arrays. Synthetic neural networks are one of the prevalent methodologies, and they have demonstrated their overall effectiveness within the context of the prediction of solar radiation. However, the currently available models of neural networks are unable to satisfy the requirements of certain one-of-a-kind scenarios, like the one that was investigated for this article. The goal of this research project is to power a racing sailboat using only non-renewable resources, such as solar panels and wind turbines. The answer that has been evolved anticipates the direct sunlight radiation on a surface that is horizontal. For this purpose, a neural community known as a Nonlinear Autoregressive Exogenous (NARX) model is utilized. We take into account every one of the sailboat operation's one-of-a-kind circumstances. The results demonstrate that first-rate prediction overall performance can be obtained even while

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 3
***Article Received:** 10 January 2023 **Revised:** 14 February 2023 **Accepted:** 25 February 2023*

the training component of the neural community is being carried out on a periodic basis (Boussaada, Curea, Remaci, Camblong, & Mrabet Bellaaj, 2018). Machine learning techniques were used to make hourly, daily, weekly, monthly, and yearly predictions about how their patterns might change.

Research Objectives of the Study

Many countries are converting to solar and wind energy to attain carbon neutrality and reduce environmental degradation targets. AIRE predicts that by 2050, renewable energy sources (solar and wind) will produce 85% of all electricity (IRENA 2018). These cheap resources have restrictions. The main disadvantage is that, unlike fossil fuels, they are weather-sensitive (Zerrahn, Schill, & Kemfert, 2018). Amounts of electricity generated by renewable resources are therefore challenging to regulate and schedule accurately. Energy production is unreliable, causing commitment concerns (Chakraborty et al., 2012). To keep the government's budget balanced, Lara-Fanego et al. (2012) recommend a good balance between power production and budgeting. So good forecasting of the amount of energy obtained from renewable resources has become increasingly important.

Several models exist to forecast renewable energy generation. Physical, persistence, AI, and statistical models are examples of these. These models can be combined to form hybrids. When used with modest alterations, machine learning (ML) is an artificial intelligence model capable of analyzing non-linear power data. Less rigidity and more adaptability than previous methods distinguish the ML technique (Santhosh, Venkaiah, Kumar, & Networks, 2019). We conducted this study since there was a lack of reviews describing ML-based predictive models.

To forecast solar and wind energy production, researchers employ machine learning-based models. An in-depth comparison of various ML algorithms for renewable energy forecasting was conducted in this work. In this way, the reader can select the most appropriate ML strategy for their needs. This study's findings will aid in the development of reliable metaheuristic optimizers and ML predictors. Also, the evaluation emphasized the challenges and the necessity for an ML-based predictive system. Both optimizers and ML tools are evaluated in this evaluation.

2. Research Methodology

A summary of renewable energy forecasts

Forecasting is predicting the future based on past facts. Global energy use is expanding rapidly, necessitating energy forecasting. Wind power is affected by air movement, air pressure, earth rotation, and geography. In the summer, the sun's rays are influenced by weather and direction forecasting energy demands can be done in several ways, as depicted below.

2.1 Time based forecasting methodologies:

There are a variety of artificial intelligence approaches to forecasting wind and solar energy generation. Some of them are illustrated in the figure.1

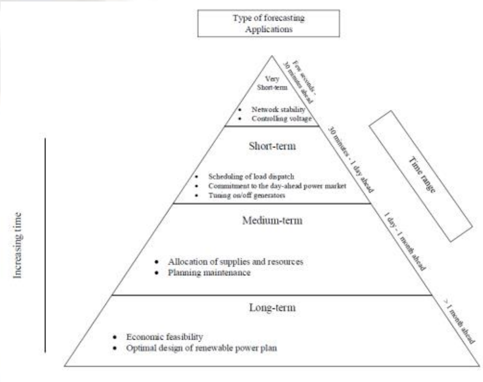


Figure.1 Time-based different methods of forecasting (Santhosh et al., 2019).

Persistence Methodologies

Persistence techniques state that the power data values are the same for the present time step and the subsequent time steps. The short-term generation of power, like 6 hours to a few milliseconds, can be accurately predicted using these methods, however the long-term generation cannot be accurately predicted using these methods (Nielsen, Joensen, Madsen, Landberg, & Giebel, 1998). Short-term forecasts benefit greatly from persistence approaches (Dutta et al., 2017)

Physical Methodologies

This strategy relies on the physical properties of the solar panels and wind turbines as well as their location. Additionally, numerical weather predictions, such as wind speed and density, pressure, temperature, turbulence intensity, and roughness, are considered (Lei et al., 2009). While these methods can be depended upon to make long- and medium-term predictions, they are not suitable for making immediate predictions (Giebel, Draxl, Brownsword, Kariniotakis, & Denhard, 2011). In addition to being exorbitant and valuable, they have no tampering and researchers, and scientists no longer use them in favor of more practical approaches.

Statistical Methodologies

Use of mathematical models based on forecasting methods is used to identify the link between the output of the targets and historical data. Ahmed, 2019 #51. The linear relation of the data is depicted using the fundamental mathematical equations (Santhosh et al., 2019). Because of the simplicity of their formulations, they are useful for short-term forecasting (Ezzat, Jun, & Ding, 2018). Moving Average and Autoregressive (ARMA) are two instances of statistical forecasting methodologies that have been combined (Jiang et al., 2018). ARMA is accurate for a wide range of applications, as demonstrated by a comparison between ANN (Artificial Neural Network) and ARMA (Erdem & Shi, 2011), (Gomes & Castro, 2012). Again (Jiang et al., 2018) looked at the It is proposed that two algorithms based on machine learning of neural networks where shallow reading (S-L) and in-depth reading (D-L) algorithms may be used in spacecraft forecasting models only to provide flow-dependent flow of ocean cooling caused by hurricane of hurricanes. A major challenge for existing SSTC algorithms in forecasting models that accurately predict SSTC is the forthcoming storm, which requires information not only from historical data but also more importantly from the target storm itself. The SL algorithm combines a single layer of neurons with a combination of space and ocean. Such a structure is found to be able to effectively represent typhoon-ocean interactions. It usually produces unstable SSTC distribution, which any disruption may lead to changes in both SSTC pattern and strength. The D-L algorithm extends the theneural network to a 4 × 5 neuron matrix with atmospheric and oceanic elements separated by indistinct layers of neurons, so that the learning machine can determine the roles of and oceanic space objects in the formation of SSTC. Thus, it produces a crescent shaped SSTC distribution, with its large-scale pattern determined mainly by atmospheric factors (e.g., winds) and small-scale elements by oceanic factors (e.g., eddies). Sensitivity tests show that D-L algorithms improve air intensity by 60–70% in four study simulations, compared to the implementation of their atmospheric model only.

Comparing the ARX and NAR photovoltaic energy models (Fentis, Bahatti, Tabaa, Mestari, & Engineering, 2019), it was found that the NAR model outperformed the ARX model in terms of performance (Bacher, Madsen, & Nielsen, 2009). Auto-regressive integrated moving average (ARIMA) was used to forecast solar energy production daily (Atique et al., 2019). ARIMA models are used to process non-stationary seasonal data before it may be further processed. By increasing the amount of the input data, this model was found to be accurate for two years in a row when forecasting wind direction and speed (Pasari & Shah, 2020). Fractional ARIMA, a particular ARIMA that can correlate between short- and long-term projections, anticipated the wind's hour of arrival before two days with a 42% accuracy rate and the models stayed employed to forecast hourly average wind speeds up to two days (48 h) ahead. The results indicate that the intended technique can enhance the accuracy of prediction. The estimated wind speeds were utilized in aggregation with the power curve of an functioning wind turbine generator to attain equivalent forecasts of the production powers. While projected errors for wind speeds further down the cut-in speed are insignificant as far as power forecasts are involved, the recommended method is noted to be advantageous for the duration of unpredictable wind speed systems. The economic impact of errors in wind turbine output power prediction on the market integration of wind farms and a systematic characterization of different wind power prediction models would be remarkable subjects for additional study. (Kavasseri & Seetharaman, 2009). Inexpensive, easy to use, and producing precise results, these statistical models last for a short time rather than a lengthy time. For the preprocessing, you'll need an AI-enabled high-end computer.

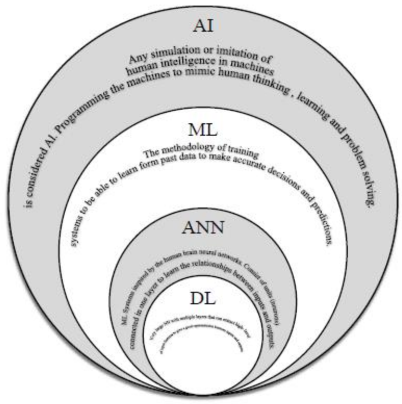
Regression Methodologies

Dependent and independent variables are both taken into consideration in these approaches. A combination of independent and dependent variables, such as solar panel and turbine operation conditions, is used to optimize the hyperparameter optimization methods. In multilinear regression models, the predictors are linked to the forecast variable using a simple linear relationship (Ahmed, Khalid, & Reviews, 2019). For the period between 1 and 6 hours before the forecast, a simple linear quantile regression model was used to build three probabilistic models to predict the solar power output (Abuella & Chowdhury, 2017). (Lauret, David, & Pedro, 2017). As an exogenous input, it was claimed that NWP (Numerical Weather Forecast) improved prediction outcomes (Piotrowski et al., 2019). Multitasking Gaussian process regression (MTGP) enhanced the NWP of wind speed (Cai et al., 2020). We were able to improve our short-term forecast accuracy by using the detailed information on wind speed we got from the NWP. These models are based on the current weather conditions. Regression spline methods were applied to historical data and forecasts of the weather to create a multilinear adaptive regression model (Massidda & Marrocu, 2017). An innovative partial functional linear regression (PFLR) model was used to predict the amount of energy generated by PV cells each day (G. Wang, Su, & Shu, 2016). It was shown that this model performed better than multilinear regression and artificial neural networks (ANN) while examining the daily data pattern. Regression approaches such as the M5 model tree (M5 Tree), Kriging, multivariate adaptive regression (MARS), and response surface method (RSM) were compared and found to be the best for predicting solar radiation (Keshtegar, Mert, Kisi, & reviews, 2018). Multiple explanatory variables can improve prediction accuracy by using regression methods. However, this relies on the input data (Akhter, Mekhilef, Mokhlis, & Shah, 2019). Its worth to mention here that Xie et al ,2019 studied a Nonparametric Bayesian framework for short-term wind power probabilistic forecast to enhance the energy system resilience and economic productivity and competency, the wind power as a renewable energy twitch to be profoundly integrated into smart power grids. However, the wind power prediction ambiguity carries operational disputes. According to (Xie et al ,2019) that the usage of fractional-ARIMA models become proposed to version and forecast hourly average wind speeds. the selection of the version become inspired by way of its potential to comprise lengthy variety correlations which were lately shown to exist in wind pace facts. The unique benefit of f-ARIMA models is their potential to parsimoniously seize time collection measurements in the presence of correlations, each quick time and long term. The models had been applied to forecast hourly common wind speeds up to two days (forty-eight h) in advance. The results advise that the proposed method is capable of improve the accuracy of forecasting (as measured with the aid of the) through an average of forty two% as compared to the staying power technique. The forecasted wind speeds had been used along with the electricity curve of an operational wind turbine generator to obtain corresponding forecasts of the output powers. whilst forecast mistakes for wind speeds under the reduce-in velocity are inconsequential as a way as energy forecasts are worried, the proposed technique is mentioned to be useful in the course of risky wind pace regimes. The monetary impact of errors in wind turbine output electricity prediction in the marketplace integration of wind farms and a scientific characterization of various wind electricity prediction models would be exciting subjects for further studies.

3. **ML-based Forecasting Methodologies**

Clustering problems, data mining, and decision-making are all handled by AI-based prediction models since they can take a significant quantity of data and execute complex tasks in a short period in various fields (Mellit, Kalogirou, 2008). Figure 2 depicts the interrelationship between the three AI subsets: ANN, ML, and deep learning (DL).

Figure 2. Relationship between artificial intelligence (AI), machine learning (ML), deep learning (DL), and artificial neural networks (ANN) (Du, Wang, Yang, & Niu, 2019)



For more accurate forecasts, machine learning (ML) methods use unstable data and non-linearity to train the computer (Jiang et al., 2018). Many machine learning approaches are commonly used to forecast the amount of energy provided by renewable resources, including support vector machines, recurrent neural networks, artificial neural networks (ANN), and extreme learning machines (ELM).

ANN-Based Methodologies

The neurons of the ANNs are organized into layers. Feature input is handled by neurons in the input layer, while neurons in the output layer deal with target analysis. This layer, located between input and output layers, contains neurons used to carry out these processes. Figures 3 and 4 depict the design of an ANN with nodes in the hidden layers and their outputs.

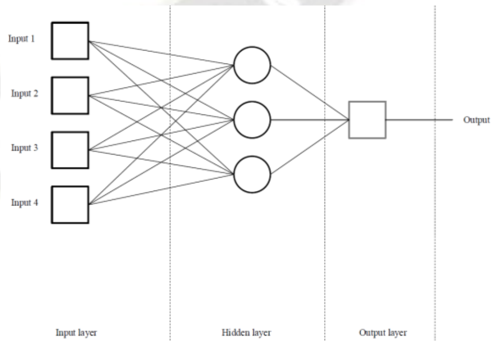


Figure 3. Node structure of an ANN where this example structure of an ANN with 4 input nodes in the input layer, 5 hidden nodes in the hidden layer and one output node in the output layer (Caio A et al ; 2019**).**

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 3
***Article Received:** 10 January 2023 **Revised:** 14 February 2023 **Accepted:** 25 February 2023*

4. ANN for Wind Power Forecasting

Models, mostly ANN, and data from the previous five years have been used to anticipate wind speed and direction (Maldonado-Correa, Solano, & Rojas-Moncayo, 2021). The feed-forward neural network (FFNN) is the simplest ANN for predicting the monthly output of 2.5 MW of wind turbine energy (Nielson, Bhaganagar, Meka, & Alaeddini, 2020). Wind density and speed were used to determine the atmosphere's stability as input in the Nielson et al. (2020) study. The mean absolute error (MAE) of wind power generated was reduced by 59% when used in place of routine estimating procedures. The RBF-NN correctly predicted the hybrid wind forecast in the RBF-NN model (Hong & Rioflorido, 2019). ANN was used by Grassi et al. (2010) to generate two hidden layers with two activation functions each (a hyperbolic tangent transfer function and a sigmoid transfer function). Inputs like metrological data and maintenance hours/month were more helpful in improving wind energy prediction accuracy. Maintenance hours, which vary from month to month, directly impact the amount of electricity generated by the model. To develop the wind speed correction model, differential equations introduced a differential polynomial function into ANN. Wavelet neural networks (WNN) are another powerful method for forecasting accurately, as they allow for rapid convergence of the data (Bashir & El-Hawary, 2000). The rough notion was used to develop a sinusoidal ANN that used the sine activation function to control the turbulence of the wind, primarily at the peaks as it was also noticed that convergence errors were minimized by utilizing a fuzzy notion using an adaptive neuro-fuzzy-based inference system. (Marugán et al., 2018). Three independent forecasts and their findings were combined into a hybrid ANFIS to predict wind power before 48 hours, exhibiting greater precision for different seasons than BPNN, RBF-NN, and LSSVM (J. Liu, Wang, & Lu, 2017).

ANN for Solar Power Forecasting

The results were influenced by data preparation, omitting night hours from the input data, avoiding data from gloomy and wet days, and the ANN training method. Weather factors such as rain, moisture, humidity, etc., influence electricity output (O'Leary and Kubby 2017). The time-domain clustering of mistakes affects the forecasting result by 1.3 percent. The NAR + ANN technique increased the monthly solar power forecast correlation factor by 9%. (Ozoegwu 2019). The inputs also shrank in size, saving memory and improving long-term predicting accuracy. Yagli, Yang, and Srinivasan (2019) compared statistical approaches and used 68 ML methods for forecasting worldwide horizontal irradiance (GHI). The same study used data from 7 meteorological stations in 5 climatic zones across the US to determine optimal prediction algorithms for each. To obtain reliable outputs, the relevant inputs were picked using neighborhood component analysis from 85 different inputs. Ghimire et al. used relative humidity, evaporation rate, specific humidity, and air temperature to make accurate predictions. A feed-forward backpropagation ANN with Levenberg–Marquardt as a training function performed better (Sitharthan, Devabalaji, & Jees, 2017).

RNNs-Based Methodologies

In addition to processing sequential data, RNN now provides temporal correlation between data (Aslam et al., 2021). In FFNN, an output is linked to an input set. The pattern of output is independent of previous outputs (Syu et al., 2020). To predict time series using RNN, we considered both the current and hidden step characteristics (Su et al., 2019). The main disadvantage of RNN is its inability to store long-term information (Bianchini, Maggini, & Jain, 2013). An exponential fall in the error gradient affects the training strategy early on (Kisvari, Lin, & Liu, 2021). A modified RNN incorporating gates for modifying information between time steps is the long short-term memory unit (LSTM). GRU has two gates, rest and update (figure 4). The update gate screens earlier stored information whereas the rest gate screens past elements (Dey & Salem, 2017).

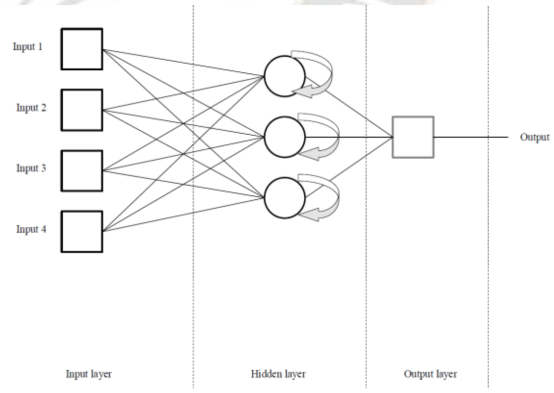


Figure 4. Schematic diagram of RNN structure (Kisvari, Lin, & Liu, 2021)

LSTM has four gates: input, forget, output, and cell state. Input and forget gates have the same inputs. The input gate transforms tan h and sigmoid functions, whereas the forget gate operates like the update gate in GRU. The input gate's output is the sum of the tan h and sigmoid functions' outputs. The forget and output gates' outputs are added to form a new cell state. It is then analyzed (figure 5)

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 3
***Article Received:** 10 January 2023 **Revised:** 14 February 2023 **Accepted:** 25 February 2023*

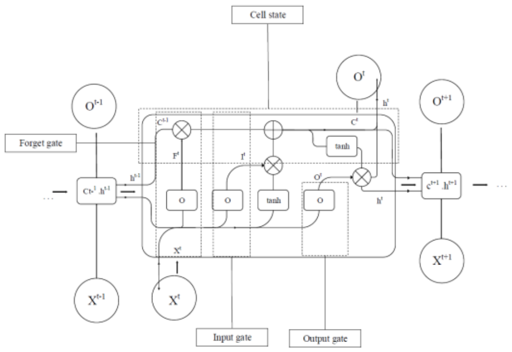


Figure 5. structure of LSTM unit whereby applied to the framework of the EV energy consumption prediction model (Guanghai Zhu, Jianbin Lin Qingwu Liu , and Hongwen He, energies, MDPI 2019)

RNN for Wind Power Forecasting

The RNN approach has been used to predict wind speed and power (Ruiz et al., 2016). The comparison can help us choose between GRU and LSTM-based RNN techniques. (Syu et al., 2020) revealed that the GRU network could forecast the wind speed 15 minutes before it happened. With its high time-series forecasting capabilities, the LSTM outperformed the GRU in a performance comparison (Kisvari et al., 2021). GRU requires more minor parameter adjustment and training time. RNN activity with an accelerated period is also poor, especially at the peaks when wind speed changes cause severe disruptions. This scenario increases GRU's durability when comparing training duration and activity to wind speed (Kisvari et al., 2021). To speed up LSTM training (convergence), we used an LSTM-enhancement forget gate (LSTM-EFG), which had two peepholes, no input gate, and calculated the updated value from the difference between the forget gate's output and one matrix's input value (Yu et al., 2019). The forget gate's direct influence hastens the process of convergence. The system was also boosted by combining temporal feature extraction and clustering techniques. Weather forecasts could not be used to schedule and control the electricity grid (Niu, Yu, Tang, Wu, & Reformat, 2020). To forecast the power of the wind at various time intervals, a single-step simulation was used to develop a multiple-input multiple-output (MIMO) model (Cruz et al. GRU attention mechanism combined with sequence-to-sequence approach selected the features. The attention mechanism analyzes the overall inputs responsible for wind power production, and the hidden GRU block activations' temporal and spatial properties are used for precision. Using this strategy decreased the problem of error accumulation significantly.

SVM-Based methodologies

Support Vector Machine (SVM) is a powerful ML technique used to solve the slightest error that emerged during the training of non-linear data and forecast the inconsistent solar and wind power values. SVM can address any local optimization problem while training ANN. However, with least-square-SVM (LSSVM), a loss function with SSE turns inequality restrictions to equality and speeds up the training process (Xingyu Z et al , 2021). The LSSVM and SVM work properly using wavelet, polynomial, linear, or radial basis kernel functions. Furthermore (Xingyu Z et al, 2021) went to study more on **growing** use of Machine Learning (ML) **additives** embedded in **self-sustaining** systems – so-**known as** Learning Enabled Systems (LES) – has resulted **withinside the urgent want** to **guarantee** their **purposeful protection**. As for **conventional purposeful protection**, the **rising** consensus **inside** both, **enterprise** and academia, is **to apply warranty instances** for this purpose. Typically **warranty instances help** claims of reliability in **help** of **protection** and **may be regarded** as a **dependent** way of **setting up** arguments and **proof** generated from **protection evaluation** and reliability modelling **sports**. While such **warranty sports** are **historically** guided **through** consensus-**primarily based totally requirements advanced** from **full-size** engineering experience, LES pose new **demanding situations** in **protection**-**vital utility because of** the **traits** and **layout** of ML models. In such work, the first **ability** on **basic warranty** framework for LES with an emphasis on quantitative aspects, e.g., breaking down system-**degree protection goals** to component-**degree necessities** and **helping** claims **said** in reliability metrics. Exhibition was the outcome to introduce **a singular version**-agnostic Reliability Assessment Model (RAM) for ML classifiers that utilises the operational profile and robustness verification **proof**. So looking at the **version** assumptions and the inherent **demanding situations** of assessing ML reliability **exposed through** our RAM and **advocate sensible** solutions. Probabilistic **protection** arguments **on the decrease** ML component-**degree also are advanced primarily based totally at the** RAM. Finally, **to assess** and **exhibit** our **techniques**, timely **no longer simplest behaviour** experiments on synthetic/benchmark datasets **however additionally exhibit** the scope of our **techniques** with a **complete** case **examine** on Autonomous Underwater Vehicles in simulation

Wind Power forecasting

The combination of polynomial and wavelet kernel functions produced a novel hybrid kernel function that improved local interpolation in the wavelet function while improving extrapolation in the polynomial function (He et al., 2019). The mean error was reduced by 3.94 percent and the dimensionality of the inputs to SVM was reduced via PCA, increasing system dependability. The MAE was reduced by 54% utilizing the density-based spatial clustering of applications with noise (DBSCAN) clustering approach (Wang X. et al., 2016). The SVM parameters are still difficult to tune and optimize**. Wang X, et al., 2016 itemised that** in addition to an explosion of **studies** on **higher know-how** of **studying** results. researchers have paid **growing interest** to leveraging interactive visualizations to **higher recognize** and iteratively **enhance** a **device studying version**. The **fundamental intention** of such **studies** is to **lessen** human **attempt while schooling** a **dependable** and **correct version**. We **confer with** the aforementioned iterative and **modern system** as interactive **version evaluation**. The **primary concept** of interactive **version evaluation**, **in which device studying fashions** are seamlessly **incorporated** with **modern** interactive visualization **strategies able to** translating **fashions** into **comprehensible** and **beneficial reasons** for an expert. The **method** is to pursue **lots of visible** analytics **strategies as a way to assist professionals recognize**, diagnose, and refine a **device studying version**. Accordingly, interactive **version evaluation targets** to create **a set** of **visible** analytics **strategies** that **recognize** why **device studying fashions** behave the **manner** they do and why they **vary** from **every** other (**know-how**); diagnose a **schooling system** that fails to converge or does **now no longer attain an appropriate overall performance** (diagnosis); and ; **manual professionals to enhance** the **overall performance** and robustness of **device studying fashions** (refinement).

Solar Power Forecasting

To manage the data volatility and noise, the SVM model is considered sophisticated machine learning (ML) (Tabari, Kisi, Ezani, & Talaee, 2012). To evaluate humid areas, SVM outperforms ANN and ANFIS (Quej, Almorox, Arnaldo, Saito, & Physics, 2017). They all employed rainfall as inputs, with similar but less dependable outputs than SVM. These models forecast solar power and PV module parameters based on four seasons (Ahmad et al., 2020). To predict solely PV power, the polynomial kernel has lower MAE and MSE than the RBF kernel.

Extreme learning machines (ELM)-Based Methodologies

It uses a single layer FFNN with Moore–Penrose generalized inverse for analysis of target results instead of the usual backpropagation approach (Akhter et al., 2019). The analysis is less difficult and requires no manual parameter adjustment (N. Li, He, & Ma, 2019). Using second-order statistics, ELM does not work with non-Gaussian or non-linear data because of the loss function. So, it's paired with another predictive technique to improve efficacy.

ELM for Wind Power Forecasting

The ELM model uses a modified loss function (Kern mean p-power error loss) to evaluate non-linear data patterns and improve model precision (N. Li et al., 2019) Because ELM's computational acceleration was limited, it was combined with other optimization techniques.

ELM for Solar Power Forecasting

This study investigated the daily and hourly generation of PV power for three grids using different ML systems (ELM, sigmoid ANN trained with the Levenberg–Marquardt algorithm, and RBF kernel SVM) (M. Hossain et al., 2017). Despite having the fastest learning speed and performance of the three strategies, ELM failed to use exogenous input data.

Metaheuristic Optimized ML Forecasting Methodologies

To improve a system's performance, Metaheuristic Algorithms (MA) are applied (Cohoon, Kairo, & Lienig, 2003). Population-based algorithms and trajectory-based algorithms are the two main forms of MA used for searching. Commonly utilized is the population-based technique, which can handle discrete and continuous functions as well as constant and transitional functions. They fail to maximize local values for general forecasting models. A huge number of experiments are required to identify the ideal network structure (Sindhu, Nivedha, Prakash, & SCIENCES, 2020). This was achieved by modifying network structure hyperparameters and tuning and estimating model parameters during training (Yang & Shami, 2020)

Metaheuristic Optimization for Tuning ML Model Parameters

The model parameters (biases, weights, and penalties of kernel functions) are tuned to improve prediction results. The parameters for a model's training process are used to improve prediction precision. The ML optimization non-convex challenges instruct the ML forecasting system to analyze minimal local parameters instead of global parameters. The Gradient Descent Algorithm (Shiliang, Zehui, Han, & Jing). A non-convex goal function will fail to achieve worldwide acceptance.

Evolutionary Optimization for Tuning ML Model Parameters

Using many solutions from the solution space, evolutionary optimization techniques analyze the approximate optimal solutions (Alba, Talbi, Luque, & Melab, 2005). This technique considers factors including mutation, reproduction, recombination, and selection. The fitness function is not predicated. So, their work is applicable to various issues.

Evolutionary Optimization Algorithms and ANN-Based Forecasting Methodologies

Three models were studied: hybrid ANN with GA, standard solo ANN, and particle swarm optimization (PSO) (Jafarian-Namin, Goli, Qolipour, Mostafaeipour, & Golmohammadi, 2019). The models were tested in MATLAB, and the hybridized ANN outperformed the solo ANN. The RMSE for PSO-ANN was 0.4385, while GA-ANN was 0.4213. (Nair, Vanitha, & Jisma, 2017). However, the conclusion that ARIMA outperformed hybridized ANN models cannot be dismissed (Nair et al., 2017). The GA-ANN model outperformed KNN, ARIMA, and ANN (Nearest Neighbour) models in predicting solar power 1-2 hours earlier (F.M.Coimbra and Hugo T.C.Pedro 2012). However, this GA-ANN technique failed to predict long-term solar power (Jafarian-Namin et al., 2019). NN, MLP-ANN, ARIMA, EVOdag, and Fuzzy forecasting were examined for predicting wind speed 1 day earlier (Flores et al., 2019)

Evolutionary Optimization Algorithms and SVM-Based Forecasting Methodologies

To tune the SVM's kernel parameters, metaheuristic techniques are used. In Spain, the SVM was combined with an Evolutionary Programming algorithm and a PSO approach to estimate wind speed (Salcedo-Sanz et al., 2011). Using a kernel function hyperparameter for tweaking the hyperparameters reduced forecasting errors and enhanced accuracy over MLP. But the accuracy was comparable to other metaheuristics. PSO, GA, and the brainstorm optimization method (BSOA) were compared to LSSVM-ideal BSOA's parameters and structure (Tian, Ren, & Wang, 2020). That swam metaheuristics are less efficient than evolutionary metaheuristics is established. Compared to PSO-SVM techniques, tweaking the penalty factor and gamma of the RBF kernel function in SVM improved wind speed forecasting (J. Wang, Zhou, Jiang, & Hou, 2015). This approach can estimate wind speed months in advance.

Evolutionary Optimization Algorithms and ELM-Based Forecasting Methodologies

ELM uses a crisscross optimization (CSO) technique to train biases and weights for predicting wind speed (Yin et al., 2017). The CSO-ELM model outperformed GA, PSO, and DE models in estimating wind ergativity and nonlinearity. The ELM was hybridized with an HBSA to estimate wind speed in a half hour (Zhang et al., 2017). With the PCA, the opposite features of input were picked using the binary backtracking search algorithm (BBSA). Optimum variational mode decomposition was used to denoise the wind data (OVMD). This system outperformed SVM, ELM, and HBSA-OVMD-SVM. Nonetheless, the ELM accelerated rate was reduced, necessitating additional research. In another BSA application, time series data were degraded and fed into three ML systems (LSSVM, ELM, and WNN) (Sun, Fu, & Li, 2019). The BSA method tweaked the model parameters, and the optimal weights were derived by combining the predictions.

Swarm-Based Optimization for Tuning ML Model Parameters

The swarm-based metaheuristics were inspired by the natural biological swarm motions where local agents interact. An ideal solution is found among a set of possible solutions in the search space (Beni & Wang, 1993). These methods were applied in medical, economics, military, and engineering (Martens, Baesens, & Fawcett, 2011)

Swarm Optimization Algorithms and ANN-Based Forecasting Methodologies

The WNN model was hybridized with four swarm optimization algorithms [multi-objective moth-flame optimization (MOMFO), multi-objective whale optimization (MOWOA), multi-objective multi-verse optimization (MOMVO) and multi-objective water cycle algorithm (MOWCA)] using four data sets (Du et al., 2019). The MOMFO algorithm outperformed the others in accuracy and stability (Du et al., 2019).

Swarm Optimization Algorithms and SVM-Based Forecasting Methodologies

The parameters for multimodal and unimodal functions were modified using the dragonfly optimization (DA) algorithm and differential evolutionary (DE) optimization (L.-L. Li, Zhao, Tseng, & Tan, 2020). 5 kernel functions were tweaked and confirmed for short-term wind power prediction. This hybrid strategy outperformed DA and other optimization methods. Another hybridized swarm optimization approach combines ALO with PSO to tune the wavelet SVM kernel function and LSTM-RNN parameters to anticipate wind speed (Vinothkumar & Deeba, 2020). Low MAE percent technique improved.

Swarm Optimization Algorithms and ELM-Based Forecasting Methodologies

Swarm optimization was used to analyze the output of three ELM networks [accelerate-PSO (APSO), PSO, and CRPSO] (Behera, Majumder, Nayak, & Technology, 2018). The APSO-ELM model produced the largest ELM output. When assessing PV power, ICSO outperformed CSO in terms of optimizing ELM biases and weights (Z.-F. Liu, Li, Tseng, & Lim, 2020).

4. Comparative Discussion for ML and Metaheuristic methodologies

We have used ML systems like ELM, ANN, SVM, and RNN to anticipate renewable energy (wind and solar) power output. Statistical assessment measures such as RMSE, MAE, R, and MSE have shown promise in the ML environment. When it comes to medium and short-term forecasting, these strategies outperform the classic methods (empirical and dynamic). To make credible predictions, ANNs analyse unstructured and non-linear data (Pedro & Coimbra, 2012). BPFF-ANN can map the non-linear trends in wind and solar energy. Compared to BP-ANN, RBF-ANN has a faster learning rate and less expense to run it the way selected and approved to be acceptable to use it. The model's dependability is tied to the network's structure or training procedure (Vinothkumar & Deeba, 2020). Parameter tweaking takes time and data.

Using FFBP-ANN, we were able to predict monthly wind power with a 59 percent accuracy (Nielson et al, 2020). The FFBP-ANN ADALINE -NN RBF-ANN measures the wind speed per hour with an accuracy of 1.1 m/s. The maintenance hours were added to the forecasting of monthly wind power generation to improve forecasting accuracy (Grassi and Vecchio, 2010). ANFIS with three different ANN approaches for forecasting wind power 48 hours ahead produced accurate results all year (Liu et al, 2017). Preprocessing the input data and clustering using FF-ANN improved the model's accuracy (Abuella and Chowdhury, 2015a). (O'Leary and Kubby, 2017) Estimated solar power per hour from ANN inputs. The monthly mean global sun radiation was computed using ANN and non-linear autoregressive modes hybridisation (Ozoewu, 2019). The hourly global horizontal irradiance was analyzed using 68 ML and statistics (Yagli et al, 2019). FFBP-ANN estimates global horizontal irradiance (Ghimire et al, 2019).

RNN uses and preserves past time step features to maintain temporal links between data (Yona et al., 2013). Although RNNs can provide effective prediction models, short-term memory difficulties make training concerns difficult. Introducing special nodes (GRU and LSTM) that may analyze data in different active mathematical functions alleviated these RNN disadvantages. Many RNN models can extract attributes from earlier time steps with more memory. These flaws cause the gradients to explode RNNs, affecting the networks' training scheme (Niu et al., 2020).

While Bayesian, random grid, and search grid optimization have reduced the time required to tune the hyper-parameters used in ML network structures, it is still a challenge. Based on our research, we propose the following improvements to ML-based forecasting:

1. The size of the data set should be increased in ANN
2. The analyzed data should be preprocessed for identification and filtering of the outliers and missing data for heightening the accuracy.
3. The results can be improved by the introduction of NWP
4. High accuracies are obtained with shorter-term forecasting horizons
5. The training process is decelerated by hybridized models of ML, although the optimization techniques improve.
6. The multistep prediction is improved by the application of metaheuristics

Suggestion for future studies

The challenges that have to be addressed, while devising further models, are as under:

1. Regional wind and solar power have been overlooked. The studies concentrate on single stations. Thus, models should be based on stations located in different areas in a particular region.
2. The Probabilistic prediction of wind energy and solar energy should be addressed in future studies for enhancing the scheduling of the electricity networks based on the estimated odd operating conditions.
3. There is a dearth of studies regarding multi-step-ahead forecasting in comparison to single-step-ahead forecasting methods, which demands attention.
4. In many studies, the mathematical correlations between the input features and the renewable

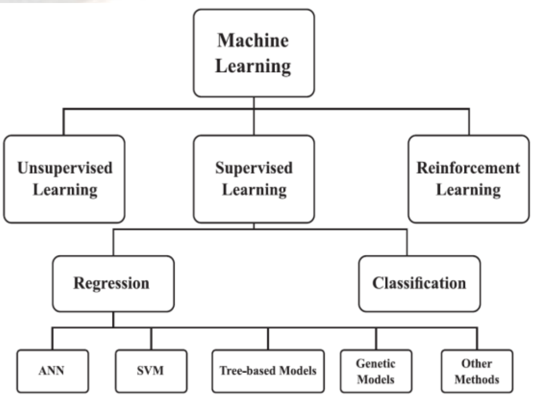
International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 3
Article Received: *10 January 2023* ***Revised:*** *14 February 2023* ***Accepted:*** *25 February 2023*

power prediction targets are not explained well. Also, the inputs which influence the nature of the forecast have not been clearly indicated. This makes a lot of potential for further research.

5. Short-term forecasting has been emphasized in most of the studies. However, there is a gap in the studies regarding long-term and medium-term forecasting. Time plays a significant role in obtaining information about the economic viability of the integration of renewable power into the electricity sector.

4.1 Machine Learning Prediction of Compressive Strength of Modern Concrete

Concrete's compressive strength is critical for design and is a factor in the load-bearing capacity of concrete constructions. The elastic modulus, tensile and flexural strength, shrinkage stresses, endurance in demanding settings, and resistance to entry of hostile chemicals are all connected to compressive strength (Gupta, 2006). The compressive strength of conventional concrete (CC) was modeled using linear and non-linear regression methods (Abdon Dantas et al., 2013; Chou and Pham, 2013; Hong-Guang and Ji-Zong, 2000). New criteria for mechanical, durability, sustainability, and resilience have led to the development of improved cementitious materials. The use of extra cementitious materials, fibers, and chemical admixtures has resulted in a more complex microstructure. Complicated non-linear relationships link the compressive strength of current advanced cementitious composites to a myriad of factors. Statistics have shown inadequate accuracy in estimating the technical features of new cementitious composites such as ultra-high-performance concrete and alkalis-activated systems. With a coefficient of determination of 0.10, Snell et al. (1989) discovered that just adding superplasticizer to combination proportions reduced the capacity of statistical models to determine compressive strength (Snell et al., 1989). Modern concrete also necessitates intricate design. However, even common concretes like HPC and UHPC, RAC, and SCC have complex mixture designs due to massive mixture components. As a result, the proportions of the mixture and the compressive strength of concrete are very nonlinear. Several experimental tests must also be conducted to better understand the complex link, requiring considerable effort and money (Deshpande et al., 2016). Artificial intelligence (AI) has recently attracted widespread attention for its extraordinary potential to solve complicated issues. AI stands for artificial intelligence (Russell and Norvig, 1995). Machine learning (ML) is a popular branch of AI that allows computers to study complex systems and make accurate predictions (Marsland, 2015). ML is a broad category of algorithms that recognize patterns in data (Murphy, 2012). It is divided into three types: supervised, unsupervised, and reinforcement learning (Figure 2-1). (Mahdavinejad et al., 2018). Regression and classification algorithms are examples of supervised learning algorithms (Murphy, 2012). Supervised techniques train the model on data with known outcomes. Unsupervised learning, on the other hand, seeks to detect relationships within data without specified labels (Murphy, 2012). Nonparametric models are unsupervised learning models (Murphy, 2012). As it determines the similarities in the data given accurate answers, reinforcement learning bridges the gap between supervised and unsupervised learning (Marsland, 2015). ML algorithms are gaining favor in several scientific domains due to their ability to detect trends in data even when none exist (Chou et al., 2014). Because of their adaptability and robustness, ML approaches have attracted a lot of attention in civil engineering. They are used for optimization and prediction (M.-Y. Cheng et al., 2014; Zewdu Taffese and Sistonen, 2017). In structural optimization, ML approaches are used to reduce the cost of a structure while maintaining performance. For example, ML can optimize structural size, topology, and shape to fulfill design criteria (Aldwaik and Adeli, 2014). Predictive algorithms, on the other hand, learn from a dataset and generalize it to make correct predictions. In civil engineering, ML methods have been used to solve problems in geotechnics, fracture mechanics, structural health monitoring, and other areas (Adeli, 200; Aldwaik and Adeli, 2014; Amezquita-Sanchez et al., 2016; Arciszewski and De Jong, 2001; Kicinger et al., 2005; Mardani et al., 2015; Nasiri et al., 2017; Penadé However, the predictive accuracy of several algorithms for normal and current concrete qualities such as mechanical, thermal, and durability has been examined and published. ML has been used to model HPC, RAC, SCC, self-healing concrete, etc (Abdon Dantas et al., 2013; Chou and Pham, 2013; Gupta, 2006; Hong-Guang and Ji-Zong, 2000; Siddique et al., 2011).



International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 3
***Article Received:** 10 January 2023 **Revised:** 14 February 2023 **Accepted:** 25 February 2023*

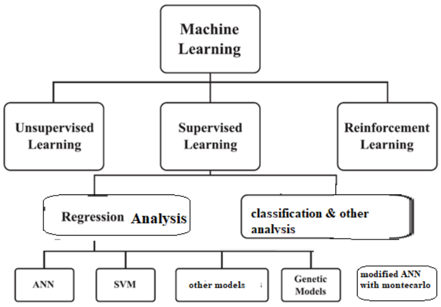


Figure 6 ML and its relation to different model

The use of ML algorithms to forecast the mechanical properties of current concrete types like as HPC, RAC, and SCC. Also, several algorithms and their hyperparameters are compared methodically. Finally, model shortcomings are identified, and suggestions for further research are made. This part provides an overview of the ML expertise required to model cementitious materials compressive strength in terms of hyperparameter tuning and evaluation measures.

Concrete production leads to increased landfills, CO_2 emissions, and loss of natural aggregates, among other negative environmental repercussions (Naderpour, Rafiean, and Fakharian 2018). It is possible to lessen the environmental impact of demolition and construction trash by reusing it (Silva et al. 2015). In spite of this, recycled aggregates adversely affect concrete qualities, particularly durability (Khaoula, Bouyahyaoui, and Cherradi 2021). In order to achieve the fundamental goal of circular economy (Sáez del Bosque et al. 2020), the elements influencing recycled concrete durability should be recognized. Reusing materials, improving concrete durability, and lowering energy usage are three vectors for developing advanced concrete technologies (Santos, Da Silva, and De Brito 2019). These vectors show a concrete strategy for long-term development. Concrete deterioration is caused by harsh environmental conditions, physical and chemical attacks (Silva et al. 2015). Concretes degrade due to carbonation assault and chloride ion penetration (Sáez del Bosque et al. 2020) The microstructure and concrete additives also impact durability. Physico-chemical response between CO2 and hydrated cement composites (Marinkovi et al. 2017). A costly concrete degradation process, corrosion of reinforcing steel So, a machine learning model was utilized to predict the level of carbonation using both outdoor exposure and accelerated carbonation experiments, respectively. With limited knowledge, machine learning can generalize data and comprehend the underlying mechanisms (Das, Suthar, and Leung 2019). In this study, four binders were studied: blast furnace slag, metakaolin, silica fume and fly ash. The resistance of recycled aggregate concrete to carbonation was tested using these binders.

5 Conclusions

Renewable energy forecasting helps maintain electrical grid stability. Power waste may be prevented, and renewable resources assist clean the environment. However, existing statistical tools have their own relevance in many aspects because they are straightforward and do not require data filtering or pre-processing. To forecast medium- and short-term events, ARIMA is used. Less trustworthy are the short-term forecasting models the physical approaches were abandoned due to their high cost and complexity. ML algorithms like ELM, RNN, ANN, and SVM use historical climate data. ANN models are good at analyzing nonlinear systems. While backpropagation and deep learning have been developed for them, overfitting and local minima still occur. The SVM simplified the arithmetic. However, SVM requires a correct kernel function. The ELM is an accelerated convergence tool ideal for simple models due to its limited feature capture and learning. The ELM must be optimized or extended to form a deep network with numerous layers. Hybridized ML systems can improve performance but take longer to execute. Because large datasets demand large data points, hybrid models have been found to be useful by combining the procedure with ANN models. It has three levels. Chemical engineers will employ deep networks in future procedures. Thus, chemical engineers sharing data will improve deep learning. Artificial intelligence (AI) will replace human operators in SCADA systems. This study also stimulates more research to improve the range of action, application, and accuracy of forecasting ML approaches and metaheuristic models.

References

1. Abuella, M., & Chowdhury, B. (2015). Solar power forecasting using artificial neural networks. Paper presented at the 2015 North American Power Symposium (NAPS).
2. Abuella, M., & Chowdhury, B. J. a. p. a. (2017). Solar power forecasting using support vector regression.
3. Ahmad, A., Jin, Y., Zhu, C., Javed, I., Waqar Akram, M., & Buttar, N. A. J. I. J. o. G. E. (2020). Support vector machine based prediction of photovoltaic module and power station parameters. 17(3), 219-232.
4. Ahmed, A., Khalid, M. J. R., & Reviews, S. E. (2019). A review on the selected applications of

forecasting models in renewable power systems. 100, 9-21.

5. Akhter, M. N., Mekhilef, S., Mokhlis, H., & Shah, N. M. J. I. R. P. G. (2019). Review on forecasting of photovoltaic power generation based on machine learning and metaheuristic techniques. 13(7), 1009-1023.
6. Alba, E., Talbi, E., Luque, G., & Melab, N. J. P. M. A. N. C. o. A. W. (2005). Metaheuristics and parallelism. 79-104.
7. Arevalo, J. C., Santos, F., Rivera, S. J. I. j. o. p., & conversion, e. (2019). Uncertainty cost functions for solar photovoltaic generation, wind energy generation, and plug-in electric vehicles: Mathematical expected value and verification by Monte Carlo simulation. 10(2), 171-207.
8. Aslam, S., Herodotou, H., Mohsin, S. M., Javaid, N., Ashraf, N., Aslam, S. J. R., & Reviews, S. E. (2021). A survey on deep learning methods for power load and renewable energy forecasting in smart microgrids. 144, 110992.
9. Atique, S., Noureen, S., Roy, V., Subburaj, V., Bayne, S., & Macfie, J. (2019). Forecasting of total daily solar energy generation using ARIMA: A case study. Paper presented at the 2019 IEEE 9th annual computing and communication workshop and conference (CCWC).
10. Bacher, P., Madsen, H., & Nielsen, H. A. J. S. e. (2009). Online short-term solar power forecasting. 83(10), 1772-1783.
11. Bashir, Z., & El-Hawary, M. (2000). Short term load forecasting by using wavelet neural networks. Paper presented at the 2000 Canadian Conference on Electrical and Computer Engineering. Conference Proceedings. Navigating to a New Era (Cat. No. 00TH8492).
12. Behera, M. K., Majumder, I., Nayak, N. J. E. S., & Technology, a. I. J. (2018). Solar photovoltaic power forecasting using optimized modified extreme learning machine technique. 21(3), 428-438.
13. Beni, G., & Wang, J. (1993). Swarm intelligence in cellular robotic systems. In Robots and biological systems: towards a new bionics? (pp. 703-712): Springer.
14. Bianchini, M., Maggini, M., & Jain, L. C. (2013). Handbook on neural information processing (Vol. 7): Springer.
15. Boussaada, Zina, Octavian Curea, Ahmed Remaci, Haritza Camblong, and Najiba Mrabet Bellaaj. 2018. "A Nonlinear Autoregressive Exogenous (NARX) Neural Network Model for the Prediction of the Daily Direct Solar Radiation" *Energies* 11, no. 3: 620. https://doi.org/10.3390/en11030620
16. Cai, H., Jia, X., Feng, J., Li, W., Hsu, Y.-M., & Lee, J. J. R. E. (2020). Gaussian Process Regression for numerical wind speed prediction enhancement. 146, 2112-2123.
17. Chakraborty, S., Senjyu, T., Saber, A. Y., Yona, A., Funabashi, T. J. I. t. o. e., & engineering, e. (2012). A fuzzy binary clustered particle swarm optimization strategy for thermal unit commitment problem with wind power integration. 7(5), 478-486.
18. Chandra, R., & Zhang, M. J. N. (2012). Cooperative coevolution of Elman recurrent neural networks for chaotic time series prediction. 86, 116-123.
19. Coddington, O., Lean, J., Pilewskie, P., Snow, M., & Lindholm, D. J. B. o. t. A. M. S. (2016). A solar irradiance climate data record. 97(7), 1265-1282.
20. Cohoon, J., Kairo, J., & Lienig, J. (2003). Evolutionary algorithms for the physical design of VLSI circuits. In Advances in Evolutionary Computing (pp. 683-711): Springer.
21. Cornejo-Bueno, L., Nieto-Borge, J., García-Díaz, P., Rodríguez, G., & Salcedo-Sanz, S. J. R. E. (2016). Significant wave height and energy flux prediction for marine energy applications: A grouping genetic algorithm–Extreme Learning Machine approach. 97, 380-389.
22. Cruz, A., Muñoz, A., Zamora, J. L., & Espínola, R. J. E. P. S. R. (2011). The effect of wind generation and weekday on Spanish electricity spot price forecasting. 81(10), 1924-1935.
23. Czarnecki, L. and Woyciechowski, P. 2012. “Concrete Carbonation as a Limited Process and Its Relevance to Concrete Cover Thickness.” ACI Materials Journal, 275–82.
24. Das, Avik Kumar, Deepak Suthar, and Christopher K.Y. Leung. 2019. “Machine Learning Based Crack Mode Classification from Unlabeled Acoustic Emission Waveform Features.” Cement and Concrete Research 121: 42–57. https://doi.org/10.1016/j.cemconres.2019.03.001.
25. Dey, R., & Salem, F. M. (2017). Gate-variants of gated recurrent unit (GRU) neural networks. Paper presented at the 2017 IEEE 60th international midwest symposium on circuits and systems (MWSCAS).
26. Ding, M., Wang, L., & Bi, R. J. P. E. S. (2011). An ANN-based approach for forecasting the power output of photovoltaic system. 11, 1308-1315.

27. Du, P., Wang, J., Yang, W., & Niu, T. J. A. S. C. (2019). A novel hybrid model for short-term wind power forecasting. 80, 93-106.
28. Dutta, S., Li, Y., Venkataraman, A., Costa, L. M., Jiang, T., Plana, R., Puttgen, H. B. (2017). Load and Renewable Energy Forecasting for a Microgrid using Persistence Technique. Energy Procedia, 143, 617-622. doi:https://doi.org/10.1016/j.egypro.2017.12.736
29. Erdem, E., & Shi, J. J. A. E. (2011). ARMA based approaches for forecasting the tuple of wind speed and direction. 88(4), 1405-1414.
30. Ezzat, A. A., Jun, M., & Ding, Y. J. I. t. o. s. e. (2018). Spatio-temporal asymmetry of local wind fields and its impact on short-term wind forecasting. 9(3), 1437-1447.
31. Fentis, A., Bahatti, L., Tabaa, M., Mestari, M. J. I. J. o. E., & Engineering, E. (2019). Short-term nonlinear autoregressive photovoltaic power forecasting using statistical learning approaches and in-situ observations. 10(2), 189-206.
32. Flores, J., Cedeno Gonzalez, J. R., Rodríguez, H., Graff, M., Lopez-Farias, R., & Calderon, F. J. E. (2019). Soft Computing Methods with Phase Space Reconstruction for Wind Speed Forecasting—A Performance Comparison. 12(18), 3545.
33. Giebel, G., Draxl, C., Brownsword, R., Kariniotakis, G., & Denhard, M. (2011). The state-of-the-art in short-term prediction of wind power. A literature overview.
34. Gomes, P., & Castro, R. J. I. J. o. S. E. D. (2012). Wind speed and wind power forecasting using statistical models: autoregressive moving average (ARMA) and artificial neural networks (ANN). 1(1/2).
35. Grassi, G., Vecchio, P. J. C. i. N. S., & Simulation, N. (2010). Wind energy prediction using a two-hidden layer neural network. 15(9), 2262-2266.
36. Hamamy, F., & Omar, A. M. (2019). Least square support vector machine technique for short term solar irradiance forecasting. Paper presented at the AIP Conference Proceedings.
37. He, J., Xu, J. J. E. J. o. W. C., & Networking. (2019). Ultra-short-term wind speed forecasting based on support vector machine with combined kernel function and similar data. 2019(1), 1-7.
38. Vinothkumar, T., & Deeba, K. J. S. C. (2020). Hybrid wind speed prediction model based on recurrent long short-term memory neural network and support vector machine models. 24(7), 5345-5355.
39. Ying-Yi Hong , Christian Lian Paulo P.Rioflorido, A hybrid deep learning-based neural network for 24-h ahead wind power forecasting, Applied Energy, Volume 250, 15 September 2019, Pages 530-539
40. Rajesh G. Kavasseri, Krithika Seetharaman, Day-ahead wind speed forecasting using *f*-ARIMA models, Renewable Energy, Volume 34, Issue 5, May 2009, Pages 1388-1393
41. Naderpour, Hosein, Amir Hossein Rafiean, and Pouyan Fakharian. 2018. "Compressive Strength Prediction of Environmentally Friendly Concrete Using Artificial Neural Networks." Journal of Building Engineering 16: 213–19. https://doi.org/10.1016/j.jobe.2018.01.007.
42. Marsland, S. (2015). Machine Learning: An Algorithm Perspective. Florida, USA: Taylor and Francis Group, LLC.
43. W. Xie, P. Zhang, R. Chen, Z. Zhou, A Nonparametric Bayesian framework for short-term wind power probabilistic forecast, IEEE Trans Power Syst, 34 (1) (2019), pp. 371-379
44. Kalogirou, S.A.: Artificial intelligence techniques for photovoltaic applications: a review. Prog. Energy Combust. Sci. 34, 547-632
45. A. Mellit and S. A. Kalogirou, "Artificial Intelligence Techniques for Photovoltaic Applications: A review," Progress in Energy and Combustion Science, Vol. 34, No. 5, 2008, pp. 574-632.
46. Jiang, G.-Q., Xu, J., & Wei, J. (2018). Adeep learning algorithm of neural network for the parameterization of typhoon-ocean feedback in typhoon forecast models. Geophysical Research Letters,45, 3706–3716. https://doi.org/10.1002/2018GL0770042018.
47. Pasari, S., Shah, A., Sirpurkar, U. (2020). Wind Energy Prediction Using Artificial Neural Networks. In: Sangwan, K., Herrmann, C. (eds) Enhancing Future Skills and Entrepreneurship. Sustainable Production, Life Cycle Engineering and Management. Springer, Cham. https://doi.org/10.1007/978-3-030-44248-4_10,
48. Marugán, A. P., F. P. G. Márquez, J. M. P. Perez, and D. Ruiz-Hernández (2018). A survey of artificial neural network in wind energy systems. Applied Energy 228, 1822–1836
49. Wang X., Liu S., Liu J., Chen J., Zhu J., Guo B. TopicPanorama: A full picture of relevant topics IEEE TVCG, 22 (12) (2016), pp. 2508-2521, 10.1109/TVCG.2016.2515592

50. Xingyu Zhao, Wei Huang, Vibhav Bharti, Yi Dong, Victoria Cox, Alec Banks, Sen Wang, Sven Schewe, Xiaowei Huang; Reliability Assessment and Safety Arguments for Machine Learning Components in Assuring Learning-Enabled Autonomous Systems; 2021,IEEE; arXiv:2112.00646v1 [cs.SE] 30 Nov 2021
51. CaioA. Custódio , Érica R. Filletti & VivianV. França ; 2019; Artifcial neural networks for density-functional optimizations in fermionic systems ; scientific reports ; https://www.nature.com/articles/s41598-018-37999-1.pdf visited 03 may 2022
52. Guanghai Zhu , Jianbin Lin , Qingwu Liu , and Hongwen He, 2019, Research on the Energy-Saving Strategy of Path Planning for Electric Vehicles Considering Traffic Information, energies, MDPI