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Forecasting Renewable Energy Generation with Machine learning: Latest Advances and Future Possibility

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Abstract: This article presents a review of current advances and future prospects in the field of fore- casting renewable energy generation using machine learning (ML techniques. With the increasing penetration of renewable energy sources (RES) into the electricity grid, accurate forecasting of their generation becomes crucial for efficient grid operation and energy man- agreement. Traditional forecasting methods have limitations, and thus ML. This paper reviews the different approaches and models that have been used for re- new able energy forecasting and discusses their strengths and limitations. It also highlights the challenges and future research directions in the field, such as dealing with uncertainty and variability in renewable energy generation, data availability, and model interpretability.
Improved irradiance forecasting ensures precise solar power generation forecasts, resulting in smoother operation of the distribution grid. Empirical models are used to estimate irradiation using a wide range of data and specific national or regional parameters. In contrast, algorithms based on Artificial Intelligence (AI) are becoming increasingly popular and effective for estimating solar irradiance. Although there has been significant development in this area elsewhere, employing an AI model to investigate irradiance in Bangladesh is limited. This research forecasts solar radiation in Bangladesh using ensemble machine-learning models. The meteorological data collected from 32 stations contain maximum temperature, minimum temperature, total rain, humidity, sunshine, wind speed, cloud coverage, and irradiance.
Finally, this paper emphasizes the importance of developing robust and accurate renewable energy forecasting models to enable the integration of RES into the electricity grid and facilitate the transition towards a sustainable energy future.

Keywords: Accurate predictions; Energy management; Machine Learning; Renew- able Energy Forecasting, solar irradiance; machine-learning; ensemble models; performance matrices; prediction error.

1. INTRODUCTION

Renewable energy development has significant advantage to gain attention due to a growing demand for pollution less and sustainable energy with low cost in recent years. However, the inherent variability and uncertainty of RES present a significant challenge for thewidespread adoption of renewable energy. For example, wind energy generation is heavily affected by the weather, which can be completely unpredictable and difficult to forecast. Similarly, solar energy generation is affected by factors such as cloud cover and seasonal changes in sunlight. The high variability and uncertainty of renewable energy generation make it challenging to integrate RES into the power grid efficiently.
One approach to address this challenge is to develop accurate forecasting models for renewable energy generation. Accurate forecasting models can help to minimize the negative impact of the variability and uncertainty of renewable energy generation on the power grid. For decades, energy generation has been predicted using traditional forecast- ing models, such as statistical models. However, these models have limitations in their ability to handle complex nonlinear relationships and the high-dimensional nature of renewable energy data.

Machine learning-based forecasting of Renewable energy

ML is a subset of artificial intelligence that seeks to enable machines to learn fromdata and improve their ability to perform particular task .The applications of ML span across diverse industries such as healthcare, finance, e-commerce, and others. In addition, ML techniques can be leveraged for predicting renewable energy generation, resulting in better

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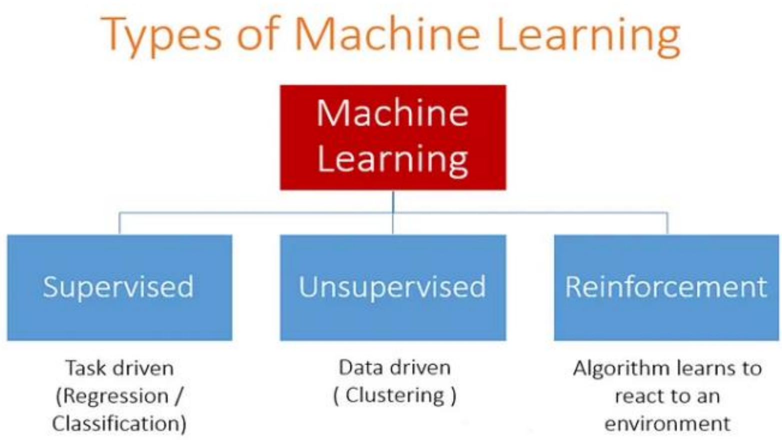
management of renewable energy systems with improved efficiency and effectiveness.

There are multiple ML algorithms available, each having distinct strengths and weaknesses. The algorithms can be categorized into three primary groups, namely supervised learning, unsupervised learning, and reinforcement learning

Supervised Learning:

Supervised learning refers to a ML method that involves training a model using datathat has been labeled. The labeled data comprises input-output pairs, where the input is the data on which the model is trained, and the output is the expected outcome. The model learns to map inputs to outputs by reducing the error between the predicted and actual outputs during training. Once trained, the model can be applied to generate predictions on new, unlabeled data. Regression and classification are the two basicsub-types of supervised learning algorithms.

a. Regression: Linear regression is a type of supervised machine learning algorithm that computes the linear relationship between a dependent variable and one or more independent features. When the number of the independent feature is 1 then it is known as Unvaried Linear regression, and in the case of more than one feature, it is known as multivariate linear regression.
The interpretability of linear regression is a notable strength. The model's equation provides clear coefficients that elucidate the impact of each independent variable on the dependent variable, facilitating a deeper understanding of the underlying dynamics. Its simplicity is a virtue, as linear regression is transparent, easy to implement, and serves as a foundational concept for more complex algorithms.
Linear regression is not merely a predictive tool; it forms the basis for various advanced models. Techniques like regularization and support vector machines draw inspiration from linear regression, expanding its utility. Additionally, linear regression is a cornerstone in assumption testing, enabling researchers to validate key assumptions about the data.,



b. Classification: Classification: It predicts the class of the dataset based on the independent input variable. Class is the categorical or discrete values. Like the image of an animal is a cat or dog?

c. Decision Trees: A decision tree is a type of supervised learning algorithm that is commonly used in machine learning to model and predict outcomes based on input data. It is a tree-like structure where each internal node tests on attribute, each branch corresponds to attribute value and each leaf node represents the final decision or prediction. The decision tree algorithm falls under the category of supervised learning. They can be used to solve both regression and classification problems.

d. Support Vector Machines (SVM): Support Vector Machine
Support Vector Machine (SVM) is a supervised machine learning algorithm used for both classification and regression. Though we say regression problems as well it's best suited for classification. The main objective of the SVM algorithm is to find the optimal hyper plane in an N-dimensional space that can separate the data points in different classes in the feature space. The hyper plane tries that the margin between the closest points of different classes should be as maximum as possible. The dimension of the hyper plane depends upon the number of features. If the number of input features is two, then the hyper plane is just a line. If the number of input features is three, then the hyper plane becomes a 2-D plane. It becomes difficult to imagine when the number of features exceeds three.

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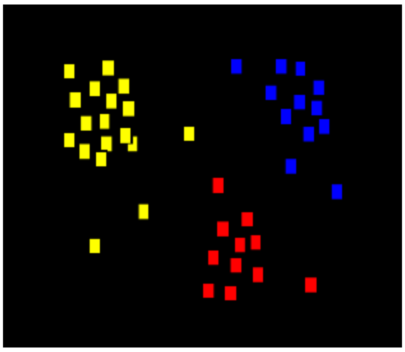
Another form of ML is unsupervised learning, where an algorithm is trained on an unlabeled dataset lacking known output variables, with the objective of uncovering pat- terns, structures, or relationships within the data. Unsupervised learning algorithms can be primarily classified into two types, namely clustering and dimensionality reduction.

e. Clustering: Cluster analysis or clustering is the task of grouping a set of objects in such a way that objects in the same group (called a cluster) are more similar (in some specific sense defined by the analyst) to each other than to those in other groups (clusters). It is a main task of exploratory data analysis, and a common technique for statistical data analysis, used in many fields, including pattern recognition, image analysis, information retrieval, bioinformatics, data compression, computer graphics and machine learning.



Cluster analysis refers to a family of algorithms and tasks rather than one specific algorithm. It can be achieved by various algorithms that differ significantly in their understanding of what constitutes a cluster and how to efficiently find them. Popular notions of clusters include groups with small distances between cluster members, dense areas of the data space, intervals or particular statistical distributions. Clustering can therefore be formulated as a multi-objective optimization problem. The appropriate clustering algorithm and parameter settings (including parameters such as the distance function to use, a density threshold or the number of expected clusters) depend on the individual data set and intended use of the results. Cluster analysis as such is not an automatic task, but an iterative process of knowledge discovery or interactive multi-objective optimization that involves trial and failure. It is often necessary to modify data preprocessing and model parameters until the result achieves the desired properties.

f. Dimensionality Reduction: The number of input features, variables, or columns present in a given dataset is known as dimensionality, and the process to reduce these features is called dimensionality reduction.

A dataset contains a huge number of input features in various cases, which makes the predictive modeling task more complicated. Because it is very difficult to visualize or make predictions for the training dataset with a high number of features, for such cases, dimensionality reduction techniques are required to use.

Dimensionality reduction technique can be defined as, "It is a way of converting the higher dimensions dataset into lesser dimensions dataset ensuring that it provides similar information." These techniques are widely used in machine learning for obtaining a better fit predictive model while solving the classification and regression problems.

It is commonly used in the fields that deal with high-dimensional data, such as speech recognition, signal processing, bioinformatics, etc. It can also be used for data visualization, noise reduction, cluster analysis, etc.

Overall, unsupervised learning is a powerful tool for analyzing large amounts of un-structured data in renewable energy forecasting. Clustering, anomaly detection, and fea-ture selection are just a few of the many applications of unsupervised learning in this field,and new techniques are continually being developed to address the unique challenges ofrenewable energy forecasting.

Reinforcement Learning Algorithms

Reinforcement learning (RL) is a branch of ML in which an agent learns to make de-cisions in an environment with the goal of maximizing a cumulative reward signal.The agent interacts with its surroundings by taking actions and receiving responses in theform of rewards or penalties that are contingent on its actions. Some examples of RLalgorithms are Q-learning, policy gradient, and actor-critic. Q-learning is a RL al- gorithm used for learning optimal policies for decision-making tasks by iteratively updat-ing the Q-values, which represent the expected future rewards for each action in each state. Policy gradient is also a RL algorithm used for learning policies directly, without computing the Q-values. Actor-critic is another RL algorithm that combines elementsof both value-based and policy-based methods, by training an actor network to generate actions and a critic network to estimate the value of those actions.
Renewable energy forecasting is among the many tasks for which RL has been uti- lized. One approach to applying RL

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to renewable energy forecasting is to use it tocontrol the operation of energy systems. For example, Sierra-García J. and S. Matilde (2020) developed an advanced yaw control strategy for wind turbines based on RL. This approach uses a particle swarm optimization (PSO) and Pareto optimal front (PoF)- based algorithm to find optimal actions that balance power gain and mechanical loads, while the RL algorithm maximizes power generation and minimizes mechanical loads us-ing an ANN. The strategy was validated with real wind data from Salt Lake, Utah, and the NREL 5-MW reference wind turbine through FAST simulations.

Renewable energy forecasting using Deep learning (DL)

DL is a type of ML that employs ANNs containing numerous layers to acquire intri- cate data representations with multiple layers of abstraction. The term "deep" refers to thelarge number of layers in these ANNs, which can range from a few layers to hundreds oreven thousands of layers . DL algorithms can learn to recognize patterns and relation-ships in data through a process known as training. During training, the weights of the links between neurons in an ANN are changed to reduce the disparity between the antic- ipated and actual output. DL has brought about significant transformations in several domains, such as energy systems, computer vision, natural language processing, speech recognition, and autonomous systems. It has facilitated remarkable advancements in various fields, such as natural language processing, game playing, speech and imagerecognition.

1. DL algorithms used for Renewable energy forecasting

ANN for Renewable energy forecasting

Artificial Neural Networks (ANNs) belong to a category of ML models that imitate the arrangement and operation of the human brain. They are devised to learn from data and utilize that knowledge to produce predictions or decisions. At a high level, ANNs consist of three main components: input layers, hidden layers, and output layers. The input layer receives the data, which is usually represented as a vector of numbers. The output layer produces the desired output of the network, which could be a classifica- tion (e.g., predicting the type of an object in an image) or a regression (e.g., predicting theprice of a house based on its features). The hidden layers are where most of the "compu- tation" happens in the network; they consist of one or more layers of neurons that performnonlinear transformations on the input data. Each neuron in an ANN receives input from other neurons or directly from the input layer. For each input, a weight is assigned that signifies the connection's potency between two neurons (Figure 2). Then, the neuron processes an activation function on the weighted sum of its inputs, which generates an output. This output can serve as the input for another neuron, and this process repeats until the final output of the output layer is obtained .
The weights within the network are modified during training to ensure that the net-work generates the intended output for a given input. This process is usually executed through a technique known as back-propagation, which determines the gradient of the loss function concerning the weights and adjusts them correspondingly. The loss function quantifies the variance between the predicted output and the actual output, and the primary objective of training is to lessen this discrepancy. ANNs are versatile and can be employed for various purposes, such as predicting renewable energy, classifying images, recognizing speech, processing natural language, and con- ducting predictive analytics .

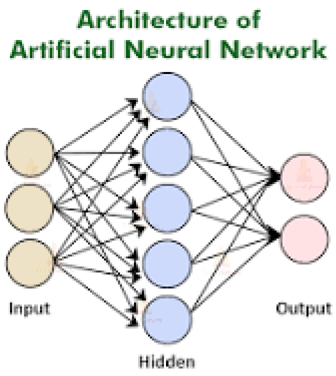

Figure 2. Artificial Neural Network Architecture**.**

ANNs have been employed in renewable energy forecasting, such as solar energy, wind energy, and multi-renewable energy forecasting, for several years, demonstrating their efficacy in this application. S. Kumar and T. Kaur (2016) used ANN to predict solar radiation for solar energy applications in Himachal Pradesh. The ANN model used tem- perature, rainfall, sunshine hours, humidity, and barometric pressure as input variables. Three models with 3 to 5 input parameters were developed and tested, with the ANN-I5 model showing the best prediction accuracy with a mean absolute percentage error (MAPE) of 16.45%. This study showed the method can also be used to identify solar en- ergy potential for any location worldwide without direct measuring instruments.
Wind energy forecasting is another important area of research in renewable energy forecasting. For instance, Jamii et al. (2022) proposed an ANN-based paradigm to forecast wind power generation and load demand using meteorological

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parameters as inputs. Re- sults showed that the ANN outperformed four other ML methods, providing high effectiveness and accuracy for power forecasting. Q. Chen and K. Folly (2019) suggested an Artificial Neural Network (ANN) model for precise short-term wind power predictionin small wind farms. Their research examines how the input variables and sample size influence the forecasting efficiency and computational expense of the model. The study investigates the effect of input variables and sample size on the forecasting performance and computing cost of the model. Their findings suggest that the ANN model with all input features and a high training sample size performs the best in terms of forecasting.

RBM for Renewable energy forecasting

Restricted Boltzmann Machines (RBM) is a type of unsupervised neural network that can learn complex probability distributions over input data. They are composed of two layers, a hidden layer and a visible layer, with each layer consisting of binary nodes that are either activated or deactivated. The training process of RBM involves contrastive divergence, a technique that works towards reducing the dissimilarity between the inputdata and the model's depiction of the data. Through training, the RBM adapts the weights connecting the visible and hidden layers to model the probability distribution of the inputdata. RBM's have several unique features that make them useful for a variety of applica- tions. Its capacity to learn high-level representations of input data without labels or su- pervision is one of their key strengths. This makes them ideal for unsupervised learning tasks like feature learning and dimensionality reduction. Another strength of RBMsis their ability to model complex dependencies between input features, which makes themeffective in modeling data with multiple interacting factors. They have been effectively employed in a wide range of fields, including image recognition, voice recognition, and natural language processing. Finally, RBMs have also been used as building blocks for more complex neural networks, such as deep belief networks and deep neural networks. In these architectures, RBMs are used to pre-train the network's layers before fine-tuningthem for a specific task .

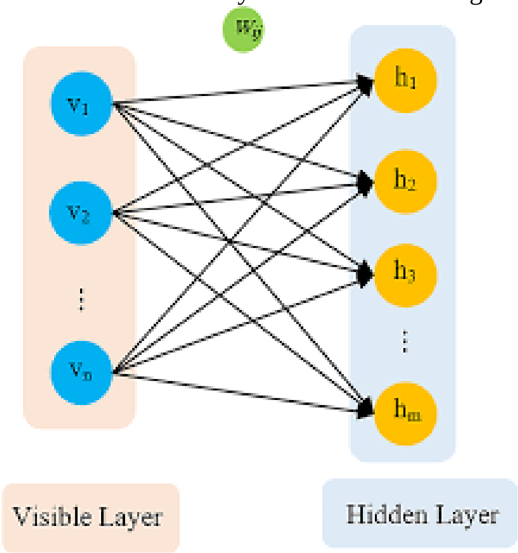

Figure 5. RBM Forecasting architecture **.**

RBMs have found applications in various fields, including renewable energy fore- casting. One such application involves using RBMs as a pre-processing step to extract fea-tures from renewable energy data before using them in other ML models such as neural networks for forecasting. Yang et al., for instance, proposed an unsupervised model for identifying irregularities in wind turbine monitoring systems that includes RBM.

Auto Encoder for Renewable energy forecasting

One of the most effective unsupervised learning models in recent decades is the au- toencoder based on a deep neural network. The unsupervised model allows for the ex- traction of effective and discriminative features from a large unlabeled data set, making this approach extensively suitable for feature extraction and dimensionality reduction [138]. Essentially, an autoencoder can be described as a neural network consisting of three fully connected layers, with the encoder containing input and hidden layers, and the de- coder containing hidden and output layers. The encoder converts higher-dimensional in-put data into a lower-dimensional feature vector. The data is then converted back tothe input dimension by the decoder. Building a complex nonlinear relationship between the input data is one of the deep neural network's top priorities since it enables the auto- encoder to successfully recreate the decoder's output. As a result, throughout the entire training period, the reconstruction error will decrease simultaneously and important features will be stored in the hidden layer. Lastly, the output of the hidden layer will showhow effectively the proposed autoencoder extracted features.

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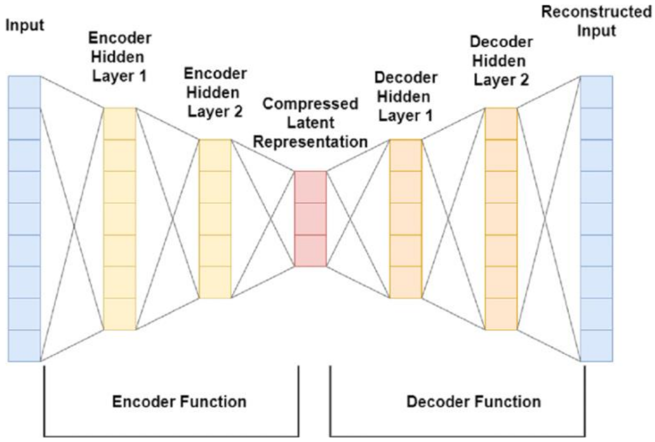
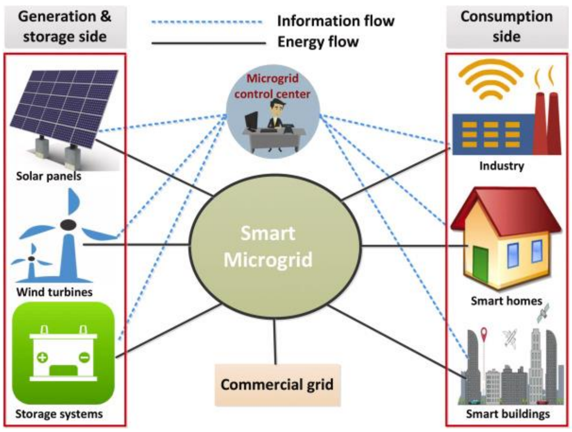


Figure 6. The autoencoder's basic design**.**

In renewable energy forecasting, autoencoder models have been used to extract fea- tures from input data such as weather data, historical energy production data, and other relevant variables. These features are then used to train ML models for energy forecasting. For example, Dairi et al., (2015) propose a Variational AutoEncoder (VAE) model for short-term solar power forecasting. The study compares the performance of the VAE- based method with seven DL methods and two ML methods using data from two PV systems. Results indicate that the VAE consistently outperforms the other methods in forecasting accuracy, highlighting the superiority of DL techniques over traditional ML methods. Jaseena and Kovoor (2015) also presented a wind speed forecasting modelthat utilizes a hybrid approach of autoencoder and LSTM. The model incorporates an au- to encoder to extract characteristics from the input data. The extracted features are then fed into an LSTM model for forecasting wind speed. Compared to other models, the pro-posed model attained superior accuracy in its forecasting.

ELM for Renewable energy forecasting

Extreme Learning Machines (ELM) was presented as a substitute for conventional gradient-based NN. ELM is designed to be computationally efficient and easy to implement, while still providing high accuracy in various applications, including regression, classification, and clustering. ELM is composed of a solitary layer of neurons that are hid-den. In this layer, the connections between the input layer and the hidden layer are gen- erated randomly and remain constant. The output layer in ELM is typically a layer that performs linear regression or classification, and the connections between the hidden layerand the output layer are determined through analytical means using matrix inversion.
ELM models are utilized for forecasting renewable energy sources (RES), including wind and solar power. For example, Li et al. (2016) suggested an ELM and error correction model to precisely predict short-term wind power. The addition of an error correction model enhanced the accuracy of ultra-short-term wind power forecasts. Hou et al. (2018) suggest a forgetting factor (FOS)-ELM model with variable forgetting factor to predict solar radiation. Using Bayesian Information Criterion (BIC), they build and evaluate seven input combinations, with the FOS-ELM model showing improved RMSE and MAE compared to classical ELM model. The study confirms FOS-ELM's effec-tiveness in daily global solar radiation simulation. Likewise, Li et al., (2019) devel- oped an ELM model to predict a wind power with kernel mean p-power error loss to overcome the limitations of traditional BP neural networks. The method eliminates redun-dant data components using PCA and achieves lower prediction error without compro- mising accuracy.



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ML approach called ensemble learning (EL) combines several models to provide predictions which are more accurate. The idea is to train several models inde- pendently on the same data, and then combine their predictions to make a final prediction.EL is particularly useful when a single model is not able to achieve high accuracy, or whenthere is significant noise or variability in the data. Bagging, boosting, and stacking are among the various types of EL techniques available. Bagging involves train- ing multiple models on various subsets of the training data with replacement. The final prediction is generated by combining the predictions of all the models. This technique is particularly useful when the base model is prone to overfitting. Boosting involves training multiple models in a sequence where each subsequent model aims to correct theerrors of its predecessor. The ensemble prediction is generated by aggregating the predic-tions of all the models. Boosting is particularly useful when the base model is prone to underfitting. Whereas in stacking, multiple models are trained and their predictions are used as input to a higher-level model that learns how to combine them. Stacking is particularly useful when the base models have different strengths and weaknesses. EL hasproven to be useful in a variety of applications, including image classification, natural language processing, and recommendation systems. However, it can be computationallyexpensive and requires careful tuning of the ensemble parameters to achieve optimal per-formance .

The Bagging technique is a popular EL method utilized in the prediction of renewa-ble energy .For example, Guia et Al. (2020) conducted a study where a Bagging- based EL technique was applied to forecast solar irradiance using weather patterns. The base learner in the ensemble was a pre-processed stacked LSTM model. The study showedthat the Bagging-based ensemble learners outperformed individual learners in terms of accuracy, as evidenced by multiple metrics. Another EL method used in renewable energy forecasting is the Boosting technique. P. Kumari and D. Toshniwal (2021) sug- gested an ensemble model for estimating hourly global horizontal irradiance that inte- grates extreme gradient boosting forest and deep neural networks (XGBF-DNN). They used a framework that incorporates feature selection and variety in base models, and thesuggested model outperforms other models in prediction error with a forecast accuracy score range of 33%-40%, making it a reliable and appropriate model for solar energy sys- tem planning and design. Al-Hajji et al. (2021) reported a comparative analysis of stacking-based ensembles for predicting solar radiation one day ahead using ML. They explored three stacking methods (feed-forward NN, SVR, and k-nearest neighbor) for merging base predictors, and assessed their performance over a year. Their findings re- vealed that stacking models, which combine heterogeneous models utilizing neural meta-models, outperformed recurrent models .

Transfer Learning (TL) for Renewable energy forecasting

TL is a ML approach in which a previously trained model is utilized as a reference point for a new task rather than developing a new model from scratch. Typically, the pre-trained model has been trained on a large dataset and has learnt useful features that can be applied to other related tasks. The TL process involves taking the pre-trained model and fine-tuning it on a new dataset for the new task. The fine-tuning process entails mod-ifying the pre-trained model by adding new layers or modifying existing layers to fit the new data. This approach assists in enhancing the efficacy of the pre-trained model for thenew task without the need to train a new model from the scratch. TL hasnumerous benefits, one of which is that it uses less data and computer resources while training new models. It also enables the use of pre-trained models that have already learned features that are relevant to the new task, which can lead to better performance than

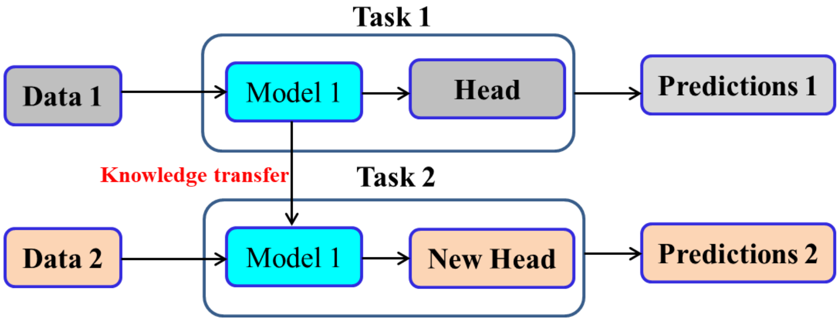

Figure 10. The schematic representation of TL.

training a new model from scratch. Several areas of ML have made extensive use of TL, including computer vision, natural language processing, and speech recogni- tion. TL has been employed in computer vision to increase the performance of picture recognition tasks including object detection, classification, and segmentation. TL has been also employed in natural language processing to increase the performance of tasks like as sentiment analysis, language translation, and named entity recognition.

In renewable energy forecasting, TL has been utilized to enhance the accuracy of re- newable energy forecasts by leveraging knowledge learned from related tasks. One com-mon approach to TL in renewable energy forecasting is to

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use pre-trained models from other related forecasting tasks. For example, Sarmas et al., (2022) propose using TL with stacked LSTM models to accurately forecast solar plant production in situations where there is a lack of data. They compared three TL models against a non-TL model and a smart persistence model, with TL models achieving significant improvements in accuracy. They conclude that TL is an effective tool for power output forecasting, particularly for newly constructed solar plants, with a view to achieving energy balance and managing demand response. Hu et al. (2016) also developed using deep neural networks trained on data-rich wind farms to extract wind speed patterns and transfer this infor- mation to newly-built farms, significantly reducing prediction errors.

Hybrid model (HM) for forecasting Renewable energy

HMs in renewable energy forecasting are ML models that combine multiple tech- niques, like ANN, SVM, and statistical models, to improve the accuracy of predictions . HMs offer several advantages over individual models by leveraging the strengths of each technique while compensating for their limitations. In renewable energy forecasting, HMsls can be employed to enhance prediction accuracy and overcome someof the limitations of classic ML models. For example, traditional models may struggle withcapturing the complex and nonlinear relationships between RES and their influencing fac-tors. HMs can address this challenge by combining multiple models and techniques to capture a wider range of features and enhance forecast accuracy.

One example of a HM used in renewable energy forecasting is the CNN and LSTM model. In a recent paper, Lim et. al. (2022) proposed a HM of a LSTM and CNN to accu- rately forecast power generation of photovoltaic (PV) systems. The model classifiedweather conditions with CNN and learned power generation patterns with LSTM. The suggested model's mean absolute percentage error was 4.58 on sunny days and 7.06 on cloudy days, indicating the possibility of precise power generation forecasting and opti- mization of PV power plant operations. Another study by Mbah et al. 2013 employed a HM for short-term power prediction of a photovoltaic plant. The model combines SARIMA and SVM methods and is tested on a 20 kWp GCPV plant. Results show good accuracy and outperform both SVM and SARIMA models. Eseye et al. (2018) em- ployed an HMs to forecast power for a real microgrid PV system over the short term (one day in advance). In terms of predicting accuracy, the model, which integrates wavelet transform (WT), particle swarm optimization (PSO), and SVM approaches, surpasses.

Challenges and Future Prospects

For predicting the output of RES like solar and wind, there are several ML and DL algorithms. Each method has its own benefits as well as drawbacks. The best ML or DL method for predicting RES depends on the specific application and available data. Linearregression can be a good choice as a baseline model, while random forest, xgboost, and SVMs are suitable for handling non-linear relationships and complex data. The variant recurrent neural networks (RNNs) models in DL are particularly useful for time-series forecasting but can be computationally expensive to train relative to classical ML models. Classical ML models can also be used for forecasting, but they may not perform as well as specialized time-series forecasting methods such as autoregressive models, moving aver- ages, and RNNs. The main reason of this is that classical ML models frequentlyassume independent and uniformly distributed data points, which is often not the case with time series data. Time series data is characterized by temporal dependencies, mean- ing that the values at one time point are influenced by the values at previous time points.The assumption that the input variables are independent of each other makes it challeng-ing for classical ML models to grasp the patterns and trends in the data. Furthermore, classical ML models are not optimized for handling time-varying features or unevenly spaced time series data, which are common in time-series forecasting. For example, a clas- sical ML model may not be able to capture seasonality or trends in the data that occur overlong periods of time.

For handling unevenly spaced time series data and identifying patterns and trends to produce precise forecasts, specialized time-series forecasting techniques like auto- regressive models, moving average models, and RNNs are the best options. Hybridmodels are becoming increasingly popular for forecasting RESs, as they can combine tra-ditional time-series analysis with ML algorithms to improve accuracy and reduce the riskof overfitting or underfitting. RNNs, in particular, are specifically designed to handle time-series data and can capture temporal dependencies to learn from long-term patternsand trends, making them a popular choice for forecasting renewable energy sources. These models have the potential to enhance the operation and development of renewable energy systems as well as their grid integration. However, forecasting RES remains chal-lenging due to their variability and unpredictability, highlighting the need for ongoing research and development of advanced forecasting techniques.

ML and DL models offer promising prospects for forecasting renewable energy sources. These models can provide more accurate predictions by processing large amounts of data and detecting complex patterns that humans may miss. These models also enable real-time forecasting to adapt to changing weather conditions, improving grid stability and enabling better decision-making. Accurate predictions also support better resource planning, leading to more efficient operations and cost savings. Furthermore, improved predictions can facilitate the integration of RES into the grid, reducing instabil- ity and enhancing overall grid performance. With careful consideration of data quality, model complexity, and validation, the use of ML and DL models has significant prospects for optimizing renewable energy operations and improving grid stability.

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CONCLUSION

There are several ML and DL methods that can be used for forecasting renewable energy sources, such as wind and solar. The choice of the most appropriate method de- pends on the specific application and available data. Classical machine learning models, such as linear regression, can be a good choice for a baseline model, while random forest, xgboost, and SVMs are suitable for handling non-linear relationships and complex data. However, specialized time-series forecasting methods such as autoregressive models,
moving averages, and RNNs are ideal for handling unevenly spaced time series data andcapturing patterns and trends to provide accurate predictions. Hybrid models that com- bine traditional time-series analysis with machine learning algorithms are also becomingincreasingly popular. Despite the challenges posed by the variability and unpredictabilityof renewable energy sources, the use of machine learning and deep learning models has significant prospects for optimizing renewable energy operations and improving grid sta-bility.

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