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Deep Learning Based Wind Power Forecasting: A Review

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***Abstract*— This paper provides an overview of recent and ongoing advancements in wind forecasting with an emphasis on fundamental ideas and real-world applications. Power system operators have several issues as a result of the high wind power penetration in the electrical system, mostly because of the unpredictable and variable nature of wind power output. Even if wind energy might not be used, power system managers can lessen the likelihood of an unstable electricity supply by using an accurate forecasting strategy for wind speed and power output. This essay provides a review of the research on the many types and primary approaches to wind forecasting. The route for future development of wind prediction is suggested based on the evaluation of wind direction and power forecasting techniques.**

Keywords*— *Wind power, wind power forecasting, support vector machines, regression methods, deep learning, machine learning, and the weibull's probability density function.

I. Introduction

One of the peculiarities is the sporadic wind. There's many times when the wind is hardly noticeable, and other times when it is easy to know it is windy just by hearing it. Wind is significantly impacted by geography. Wind is typically stronger at the beach due to the difference in atmospheric temperature between the land and the ocean. A similar situation—a temperature difference, in this instance between a mountain and a valley—results in a similar occurrence, increased wind speed around specific valleys. Seasonal variations in wind patterns result in stronger winds being more frequently observed in India in the spring. The role of wind power forecast has grown increasingly important as the rate of wind penetration increases. Every power system has a reasonable ability to react to changes in demand since demand estimation is never precise. Power systems do not need to be worried with the fluctuation of the wind power supply when the penetration rate is low. This is due to the fact that, for instance, a decline in wind speed that results in a reduction in the supply of wind energy is quite comparable to an increase in demand, which even the power system can handle.

II. Literature REview

Saroha et. al. introduced the Linear Neural Network classifier with Tapped Delay (LNNTD) in conjunction with Wavelet Transform (WT) for stochastic wind power forecasting in a time series context with the goal of increasing wind power prediction accuracy and dependability. In order to compare outcomes, the benchmark model, several neural networks, and WT-based models are used, taking performance metrics like accuracy, execution time, and R2statistic into account. The probabilistic forecast qualities at several skill tests are highlighted in this research in order to demonstrate the validity and reliability of the proposed model. The experimental findings unmistakably demonstrate that the suggested model's outcomes have been proven to be superior to others.[1]

Gupta et. al. the methods for predicting solar irradiance in the literature were examined. The primary goal of the study was to determine how meteorological variables, time spans, climate zones, pre-processing methods, optimization, and sample size affect the model's level of complexity and accuracy. Artificial neural network-based reputation as a leading other systems in the literature because of their nonlinear complex problem-solving abilities. Even more accuracy can be achieved by combining the two models or by doing pre-processing on the incoming data. Additionally, it discusses the different key elements that affect a model's accuracy. In order to choose the best model for a particular location, the study presents essential conclusions based on reviewed literature. The criteria employed to gauge the effectiveness of the projected model are also covered in this study. It has been shown that choosing the right training and testing periods helps the model's accuracy.

Singla et. al. focuses on examining how the model's complexity and accuracy are affected by meteorological variables, timeframe, climatic zone, which was before techniques, air pollution, and sample size. The model results and all-important parameters were presented in a tabular format with the publication year, temporal resolution, input parameters, projected variables, error metrics, and performances in order to make the article reader-friendly. The research revealed that ANN-based model performs better the competition because of their capacity for nonlinear complicated problem-solving. The two models can be combined to increase their accuracy, or the input data can undergo pre-processing. Additionally, it talks about the several important factors that influence a model's accuracy. It has been shown that choosing the training and testing periods wisely, as well as using dependent variables that are associated, increases the model's accuracy.

Sakthivel et. al. focused on the challenge of designing a finite-time reliable filter for discrete-time Takagi-Sugeno fuzzy semi-Markovian jump networks with time-varying latency, sensor errors, and unpredictable uncertainties. To be more specific, a semi-Markov process accurately describes the time-varying state transition matrix for the system under consideration. The goal was to provide a dependable filter that will guarantee the enhanced filtering error system's rigorous dissipativity performance in the case of sensor failures. Furthermore, it is expected that the stochastic variables that characterise the randomness of the parametric uncertainty adhere to the Bernoulli distribution. For the Takagi-Sugeno fuzzy semi-Markovian jump systems under consideration, a novel finite-time stochastic stability criteria based on key principle convex approach and Lyapunov-Krasovskii stability theory is constructed in terms of linear matrix inequalities. Additionally, the delay-dependent requirements are set up to ensure that the enhanced filtering error system is stochastically bounded bounded and that it meets a predetermined tight dissipativity performance level for all permitted uncertainties and sensor flaws.

Colak et. al. reviewed the research on very short-, short-, medium-, and long-term wind power projections is presented in this work. Studies that have been published in the literature have been assessed and criticized in light of the accuracy and completeness of their predictions. It has been demonstrated that multilayer perceptron's, neural networks, and adaptive neuro-fuzzy sources. Secondary data produce superior forecasts for wind energy.[2]

Chen et. al. presented a novel techniques to enhance and maximise the production of sustainable wind energy, precise wind speed prediction is becoming ever more crucial. Particularly, accurate short-term wind speed forecasts can support predictive modeling of wind generators and real-time wind farm operation optimization. Due to the substantial stochastic character and dynamic uncertainty in wind speed. In order to properly modify the short-term estimate of wind speed sequence, Unscented Kalman filter (UKF) and the support vector regression (SVR) based it as were merged. Support vector regression was used to create a nonlinear state-space model in the proposed SVR-UKF technique, and unscented Kalman filter was used to conduct dynamic state estimation on a wind sequence repeatedly with stochastic uncertainty. For the purpose of forecasting short-term wind speed sequences gathered from three sites in Massachusetts, USA, the innovative SVR-UKF technique was compared with neural networks (ANNs), SVR, autoregressive (AR), and autoregressive combined with Kalman filter (AR-Kalman) methods. The forecasting results show that the suggested technique performs much better than other approaches across all sites inside one and inter wind speed forecasts.

Shobana Devi et. al. proposed a unique method based on LSTM (Long Short-Term Memory) to anticipate wind power 1 to 6 hours in advance. In contrast to the traditional LSTM method, a recursive technique was employed to forecast short-term wind power. Utilizing historical data on wind energy production for Gujarat state, the suggested model is put into practise. The suggested R-LSTM (Rolling-LSTM) model beat the previous strategy with less error and improved accuracy, according to a comparative study of the approaches provided in the literature.

Damousis et. al. proposes a fuzzy model for forecasting wind speed and electrical power output in wind parks. A learning strategy based on genetic algorithms was used to train the model. Data on wind direction and [7]speed that were collected at locations up to 30 km from wind turbine clusters were included in the training set. Two application instances with extensive simulation results were presented, including wind speed predictions from 30 min to 2 h in advance. It was shown that the recommended model significantly outperforms the persistent approach while achieving a sufficient grasp of the issue.

Monfared et. al. suggested to use fuzzy logic and artificial neural networks to estimate wind speed. In comparison to the old fuzzy logic approach, the [8] new one not only offers a substantially smaller rule base but also improves the accuracy of the anticipated wind speed. Applying the suggested method to an artificial neural network results in fewer neurons and a quicker learning process along with accurate wind speed prediction outcomes. The experimental findings show that the suggested strategy not only requires less computational time, but also performs better when predicting wind speed.

Hanifi et. al. discusses the uncertainties and variations in wind speed are the main barrier preventing a further penetration of wind power into the electrical system. The state-of-the-art methods for wind power forecasting were carefully evaluated, covering physical, statistical (time series and artificial neural networks), and hybrid approaches. Accuracy and computing time in predictive modelling attempts were also taken into consideration. Additionally, guidelines for the screening of the wind power forecasting process, enabling the operators of wind farms and turbines to choose the most suitable predictive techniques based on factors such as time horizons, input features, computational time, error measurements, etc.

III. CONCLUSION

This study analysed research on wind power prediction model critically, concentrating on analytic techniques, prediction time frames, error measures, and accuracy enhancements. Physical approaches are more difficult and need significant computational resources, but they are acceptable for medium- to long-term prediction under the same circumstances. On the contrary hand, statistical methodology were cheap and simple to model, and they performed better over short to medium periods of time. The promising hybrid techniques were created by combining these two main approaches and their advantages. The most often utilised input characteristics in the research that were analysed were temperatures, wind direction, relative humidity, and air pressure in addition to wind speed. The 10-minute sample interval and the one-year time frame were also the most often used characteristics for input data. A chart for wind energy prediction is proposed based on the talks in this work, allowing users to choose the best prediction approach based on various time horizons, analytical methodologies, error measures, etc.

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