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Particle swarm optimization-extreme learning machine model combined with the AdaBoost algorithm for short-term wind power prediction

Ganesapandiyan Ponkumar[1], Subramanian Jayaprakash[1], Dharmaprakash Ramasamy[2], Amudha Priyasivakumar[2]
[1]Department of Electrical and Electronics Engineering, Sathyabama Institute of Science and Technology, Chennai, India
[2]Department of Electrical and Electronics Engineering, Panimalar Engineering College, Chennai, India

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ABSTRACT

In our proposed approach, we integrate AdaBoosting with particle swarm optimization-extreme learning machine (PSO-ELM) to enhance the accuracy of wind power estimation, addressing the inherent unpredictability and variability in wind energy. Initially, we refine the thresholds and input weights of the extreme learning machine (ELM) and then construct the PSO-ELM prediction model. AdaBoost is utilized to generate multiple weak predictors, each comprising a distinct hidden layer node. The PSO technique is then employed to optimize the input weights and thresholds for each weak predictor. The final forecast is attained by amalgamating and weighting the outcomes from each weak predictor using a robust wind power forecast model. Experimental validation utilizing data from Turkish wind turbines underscores the efficacy of our approach. Comparative analysis against contemporary techniques such as ensemble learning models and optimal neural networks reveals that our ADA-PSO-ELM model demonstrates superior accuracy and generalizability in predicting wind power output under real-world conditions. The proposed approach offers a promising framework for addressing the challenges associated with wind power estimation, thereby facilitating more reliable and efficient utilization of wind energy resources.

Corresponding Author:

Ganesapandiyan Ponkumar
Department of Electrical and Electronics Engineering, Sathyabama Institute of Science and Technology
Chennai, India
Email: ponkumar21@gmail.com

1. INTRODUCTION

Wind power is currently the forefront of renewable energy technologies, particularly in terms of business models. The Asia-Pacific region leads globally with a wind power capacity exceeding 347 GW, as reported by the global wind energy council (GWEC) [1]. However, the inherent unpredictability of wind power poses challenges for maintaining a stable and secure power system. Accurate wind power forecasts are essential for reducing grid transmission costs and enhancing system efficiency. Medium-term forecasts, spanning weeks or months, are crucial for maintenance planning, while long-term forecasts, spanning a year, are used for annual power planning. Yet, research on the accuracy requirements of these forecasting techniques is limited [2]-[4].

Short-term forecasts, typically spanning three days, and ultra-short-term forecasts, covering the upcoming 10-4 hours, are vital for cost-effective load distribution and rotational reserve optimization in the wind power industry. Time series forecasting for wind power generation systems has gained significant attention recently [5]-[7]. Sharma and Singh proposed using a long short-term memory (LSTM) neural network, which utilizes k-means clustering on historical wind power data to create a comprehensive training set for future predictions. Wavelet techniques were employed to divide wind force time series into subsequences, and the kernel extreme learning machine (KELM) was used for forecasting, with the final prediction integrating output data. Hong et al. introduced three ensemble learning models—improved tree, random forest, and augmented random forest—for wind energy prediction. Lin and Luis utilized the variational mode decomposition (VMD) technique to preprocess historical power series before employing LSTM for prediction and fusion of subsequences. Additionally, Wang *et al.* proposed processing wind power time series using wavelet decomposition and employing support vector machines (SVM) to estimate wind power for the final day of the week. These methods, based on time series analysis, demonstrate the ongoing efforts to enhance wind power forecasting accuracy and reliability [8]-[11].

Short-term wind power estimation methods typically fall into two categories: statistical and physical models. Physical models rely on dynamic and thermodynamic equations related to meteorological development, considering factors such as latitude, height, and terrain. However, these models are complex, require significant processing, and are sensitive to initial data accuracy [12]. In contrast, statistical models create forecasts based on training samples and new input measurements, offering broader applicability due to their ability to handle non-linear correlations. Recent efforts in wind power forecasting have focused on statistical models, with support vector machines (SVM) and neural networks demonstrating success. Techniques like particle swarm optimization have been employed to enhance SVM performance, while neural networks have been trained using historical climate and wind data for short-term forecasting. Additionally, methods like empirical mode decomposition combined with neural networks have been proposed for reconstructing wind speed time series.

The extreme learning machine (ELM) has emerged as a promising tool for wind power forecasting due to its rapid training speed and strong generalization abilities. Optimization techniques, such as genetic algorithms and artificial fish shoal methodology, have been applied to improve ELM's prediction accuracy by adjusting input parameters. AdaBoost, a collaborative learning strategy, has been utilized to enhance model performance by iteratively training weak predictors and integrating them into strong predictors. This approach has been combined with PSO-ELM for wind power prediction, where particle swarm optimization is used to optimize model inputs, and AdaBoost is employed to integrate weak predictors. Real data is then used to train the proposed model, and its performance is compared to existing models to assess improvements. The article is structured into sections detailing the ADA-PSO-ELM wind power prediction model, training methodology, and comparative analysis of forecast results, demonstrating the effectiveness of the proposed strategy [13]-[17].

2. METHOD

The integration of wind power into the grid faces significant challenges due to the inherent uncertainty and variability in wind speed. Accurately predicting wind energy generation is crucial for the efficient functioning of the power system, impacting decisions such as unit commitments, maintenance scheduling, and profit maximization for power dealers. The advancement of reliable wind forecasting methods is essential for cost-effective operation and maintenance of wind turbines [18]-[20]. This study systematically investigates the current state-of-the-art approaches to wind power forecasting, encompassing physical, statistical (including time series analysis and artificial neural networks), and hybrid methods. It examines factors influencing forecasting accuracy and computation time in predictive modeling efforts. Furthermore, the study offers guidelines for evaluating wind power forecasting processes, aiding wind turbine/plant operators in selecting the most suitable forecasting method based on factors such as the time period of interest, input features, computation time constraints, and error metrics. By providing a comprehensive review and guidance, this study contributes to the improvement of wind power forecasting practices, ultimately facilitating the efficient integration of wind energy into the power grid and enhancing the overall reliability and sustainability of energy systems [21], [22]. Figure 1 shows the block diagram of wind energy system.

A dataset serves as a repository of various digitally stored data types essential for machine learning endeavors. It encompasses unprocessed information accumulated throughout the research process, often in numerical form. Many entities, including governmental agencies, academic institutions, and research centers, provide publicly accessible data online for use by researchers [23]-[25]. Platforms such as Wordpress.com, Google Dataset Search, Kaggle, Data.Gov, and the UCI machine learning repository are commonly utilized for sourcing datasets. Figure 2 shows AdaBoost algorithm for predicting wind power. Data preparation, a critical initial step in machine learning, involves transforming unstructured data into a usable format for machine learning algorithms. However, acquiring structured and clean data suitable for machine learning applications can be challenging. The methodology for developing artificial intelligence models typically involves training the model using labeled data, known as the training set. For instance, in creating a self-driving car model, the training data comprises labeled images and videos depicting vehicles, traffic signs, and pedestrians. The training set consists of pairs of input patterns and corresponding desired output patterns, illustrating how the network responds to specific inputs. Adjustments to the network's weights are made iteratively to minimize errors until the desired level of accuracy is achieved. Following training, a separate dataset known as the test set is employed to impartially evaluate the performance of the machine learning model. This secondary or tertiary dataset helps gauge the model's effectiveness after training on the initial dataset, ensuring unbiased assessment of the final model.

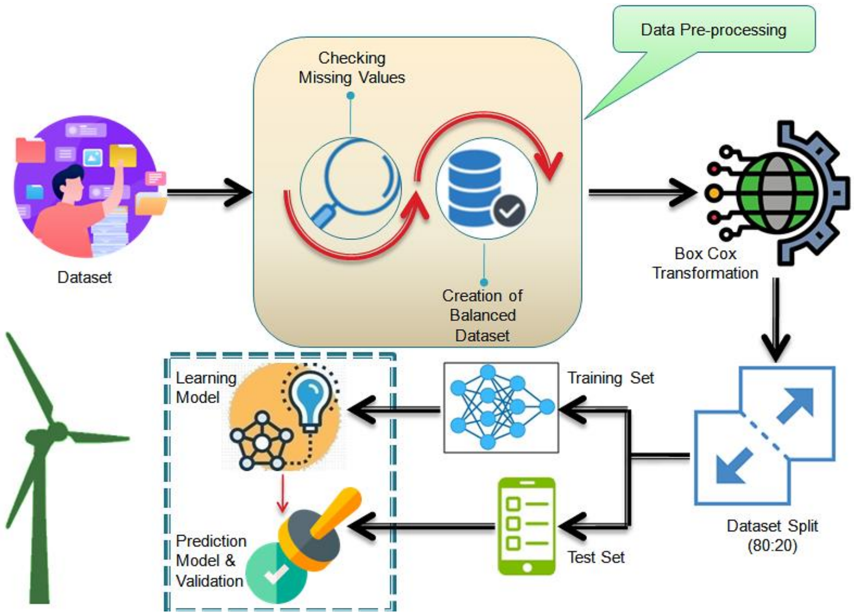


Figure 1. Block diagram of wind energy system

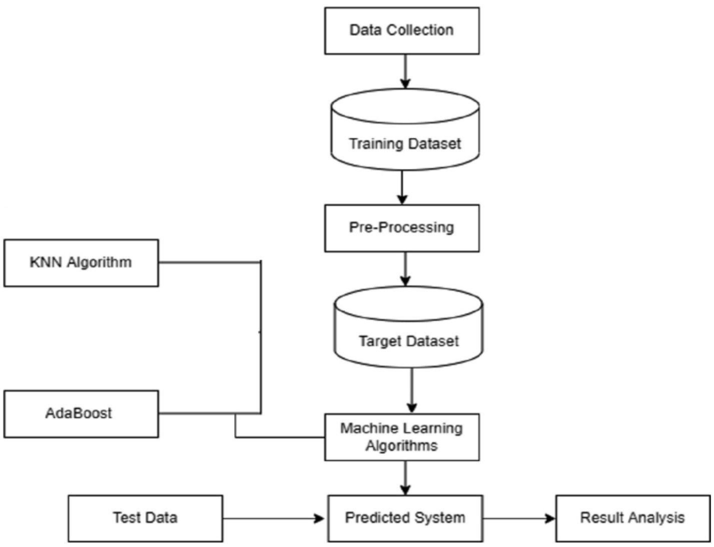


Figure 2. Shows ADA boost algorithm for predicting wind power

The performance metrics mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE) and R-squared value [17] have been defined in (1) to (4).

$$MAE = \frac{|(y_i - y_p)|}{n} \tag{1}$$

$$MSE = \frac{\sum(y_i - y_p)^2}{n} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum(y_i - y_p)^2}{n}} \quad (3)$$

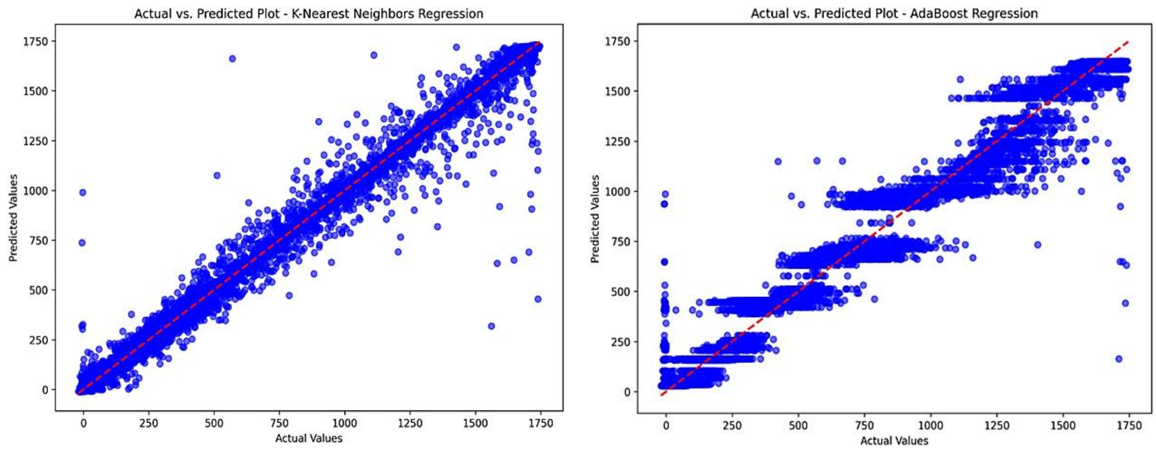
$$R^2 = 1 - \frac{\sum(y_i - y_p)^2}{\sum(y_i - \overline{y_i})^2} \quad (4)$$

3. RESULTS AND DISCUSSION

The regression model was created using two machine-learning algorithms namely kNN regression and AdaBoost. To predict the active power output for a new data point, the kNN model finds the k-nearest neighbors in the training dataset (based on a distance metric, often Euclidean distance), where k is a user-defined hyperparameter [24]. The predicted value is then calculated as the average (in case of regression) or the majority class (in case of classification) of the k-nearest neighbors.AdaBoost assigns weights to each data point in the training dataset. Initially, all data points have equal weights. In each iteration, a new weak learner (a simple decision tree) is trained using the weighted data [25]. The model then evaluates its performance and assigns higher weights to misclassified data points. This process continues for a predefined number of iterations or until the model reaches a desired level of performance.

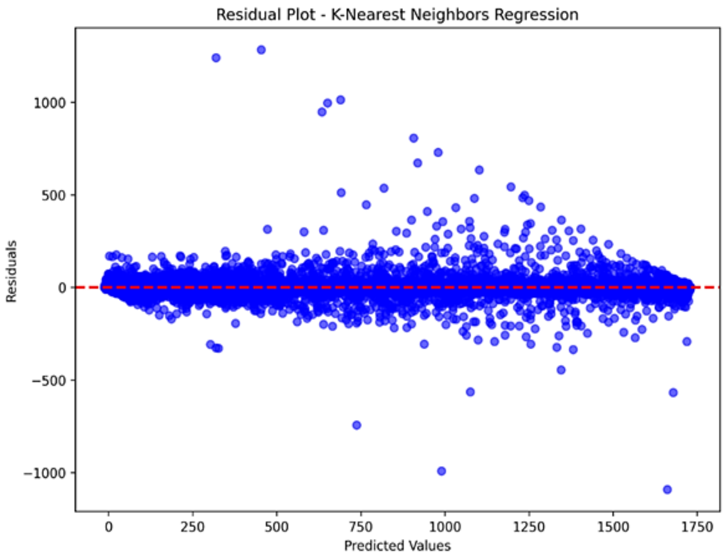
The kNN model performs exceptionally well in capturing local patterns and complex relationships, leading to high accuracy in prediction. On the other hand, AdaBoost regression benefits from its ensemble nature, effectively handling complex and noisy data, although it may not capture local patterns as well as kNN.Table 1 presents the performance of two wind power prediction models, namely k-Nearest neighbors regression and AdaBoost regression, on the test set. Figures 3(a) and 3(b) display the predicted and actual values for both machine learning models, k-nearest neighbors regression and AdaBoost Regression, respectively. The plots show how well the models are able to predict wind power compared to the actual observed values.

Figures 4(a) and 4(b) display the residual plots for the two models, aiding in the visualization of error distribution and identification of any discernible patterns or trends in model performance. The analysis reveals the k-nearest neighbors regression model's exceptional performance, boasting a high R-squared value of 0.995. This value indicates that 99.5% of the variance in the wind power data is accounted for by the model. Meanwhile, the AdaBoost regression model also demonstrates commendable performance, with an R-squared value of 0.978, explaining 97.8% of the variance in the wind power data. The comparison of predicted and actual values plotted in Figures 3(a) and 3(b) illustrates that both models generally capture the trends and patterns within the wind power data. However, a closer examination of the residual plots in Figures 4(a) and 4(b) reveals certain variations and errors in predictions, particularly evident in the AdaBoost model where residuals exhibit a wider spread.

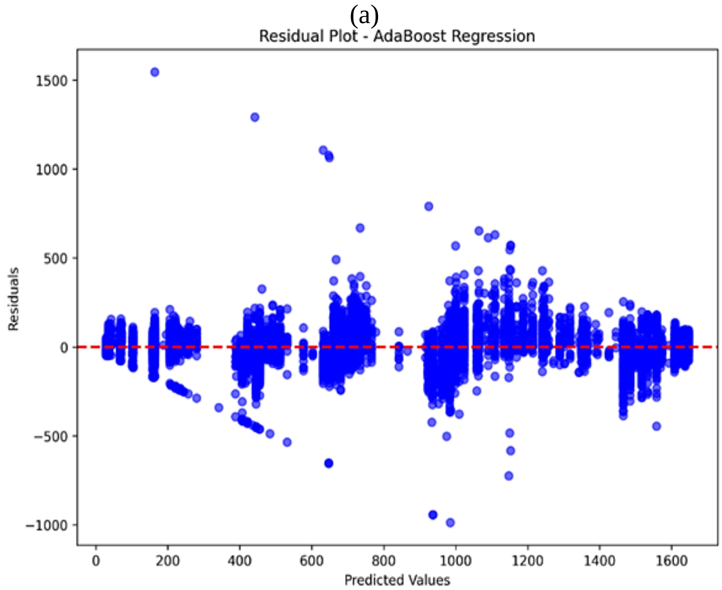


(a) (b)

Figure 3. The predicted and actual values plot of machine learning models: (a) k-nearest neighbors' regression and (b) AdaBoost regression



(a)



(b)

Figure 4. The residual plot of machine learning models: (a) k-nearest neighbors' regression and (b) AdaBoost regression

Further analysis based on performance metrics such as mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and R-squared values indicates that the k-nearest neighbors regression model outperforms the AdaBoost Regression model in terms of accuracy and precision. The lower values of MAE, MSE, RMSE, coupled with the higher R-squared values, suggest superior predictive capability of the kNN regression model. Consequently, in the context of this study, the k-nearest neighbors regression model emerges as the more suitable choice for wind power prediction.

Table 1. Wind power prediction models' performance on test set

Model Name	MAE	MSE	RMSE	R^2
kNN Regression	14.772	1753.812	41.878	0.995
AdaBoost	64.597	8025.892	89.587	0.978

4. CONCLUSION

Wind power prediction plays a critical role in efficiently integrating wind energy into the power grid and ensuring a reliable electricity supply. Accurate predictions enable grid operators to predict fluctuations in wind power generation, balanced distribution of electricity, and optimize the use of various resources, thus minimizing operational costs. Additionally, wind power predictions are vital for electricity generators to participate effectively in energy markets and avoid financial penalties for deviations between scheduled and actual electricity production.

This article investigated wind power prediction using machine learning algorithms, particularly k-nearest neighbors regression and AdaBoost regression. The kNN model showed exceptional performance, with an R-squared value of 0.995, indicating its ability to explain 99.5% of the variance in wind power data. On the other hand, the AdaBoost regression model achieved an R-squared value of 0.978. Both models captured the general trends in wind power data, but the kNN model outperformed AdaBoost in terms of accuracy and precision.

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BIOGRAPHIES OF AUTHORS

Ganesapandiyan Ponkumar completed B.E. Degree in Electrical and Electronics from Anna University 2011, M.E. Degree in Power system from Anna University 2013 and pursuing Ph.D., in Sathyabama Institute of Science and Technology, Chennai, Tamil Nadu, India. He has experience of more than 10 years in teaching. He has published many technical papers in various journals and conferences. He is currently working as Assistant Professor in Panimalar Engineering college, Electrical and Electronics Engineering. His research focus is on Artificial Intelligence, Power system, Electrical machines, Power Electronics, Renewable energy, DC and AC drive applications, intelligent techniques in power electronics and drives, and other related topics. He can be contacted at email: Ponkumar21@gmail.com.

Subramanian Jayaprakash completed Diploma in Electrical and Electronics Engineering, DOTE, Chennai, in 1996, B.E. Degree in Electrical and Electronics from the University of Madras in 1999, M.E. Degree in Power Electronics and Industrial Drives from Sathyabama University in 2007 and obtained his Ph.D., from Sathyabama Institute of Science and Technology in 2018, Chennai, Tamil Nadu, India. He has experience of more than 13 years in teaching and more than 3 years industrial fields. He has published more than 20 technical papers in various journals and conferences national, international and 2 granted Patent. He is currently the Assistant Professor at School of Electrical and Electronics Engineering at Sathyabama Institute of Science and Technology. He is a member of International Association of Engineers and life member of Indian Society for Technical Education. His research focus is on electrical machines, power electronics, renewable energy, DC and AC drive applications, intelligent techniques in power electronics and drives, and other related topics. He can be contacted at email: jakash2109@gmail.com.

Dharmaprakash Ramasamy has Obtained B.E. in Electrical and Electronics Engineering from Bharathiyar University in 1998, M.E. in Power Electronics and Drives from Bharathidasan University in 2000 and Ph.D. from JNTU Hyderabad in 2016. He has authored more than 50 papers published in international and national conference proceedings and technical journals in the area of power Electronics. Presently he is working as Professor in Panimalar Engineering College, Chennai. He has a total teaching experience of 23 years. His areas of interest are power converters, inverters, AC drives, renewable energy, and electric vehicles. He can be contacted at email: rdharmaprakash@yahoo.co.in.

Amudha Priyasivakumar is working as an Assistant Professor in Electrical and Electronic Engineering Department, Panimalar Engineering college, India. She received her B.E. degree in Electrical and Electronics engineering and the M.E. degree in power electronics, both from Anna University and St. Peters University, Tamil Nadu, India. Her research interests include the field of power electronics, motor drives, industrial applications, industrial electronics, photovoltaic power systems, digital design, front-end RTL logic design, and field programmable gate array applications. She can be contacted at email: amudhapriya.21@gmil.com.