Wind Speed Prediction using Gaussian Process Regression: A Machine Learning Approach

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***Abstract*— Wind power is a challenge in power generation. The tortuous process stages in generating voltage become a significant problem to be solved properly. One indicator of the process is the determination of the right wind speed because it always changes at any time and under circumstances. For this reason, accurate predictions are needed so as to maintain the smooth integration of wind power into the overall system. Machine learning is used as a promising approach to dealing with wind intermittent power because wind speed prediction methods have been developed in recent years. This study explores climate patterns in the Philippines using data collected from PAGASA. The data is trained and tested with a machine learning model to predict wind speed. This research resulted in the Gaussian Process Regression (GPR) model outperforming other models and is very suitable for datasets in achieving accurate and reliable predictions.**

Keywords*— gaussian process regression, machine learning models, PAGASA, wind power, wind speed prediction

I. INTRODUCTION

Traditional energy sources are very depleted by the influence of environmental factors. Currently, a new energy source that can be used widely is urgently needed, namely wind power. Wind power has the characteristics of being clean, efficient and sustainable so that it becomes an important contributor in electricity generation [1][2]. However, utilities that largely rely on wind energy face considerable issues since wind power is unreliable [3]. Accurately predicting wind speeds is essential to optimize the utilization of wind energy, determine appropriate turbine sizes, and select suitable sites [4].

Machine learning techniques have shown promise in addressing the intermittency of wind power by accurately forecasting wind speeds. This capability enhances system safety, optimizes dispatch, and minimizes economic losses [5][6]. Wind speed prediction is very important in supporting turbine load and scheduling effectively to optimize operating costs. Wind speed forecasting is essential for predicting load and scheduling wind turbines effectively, which reduces spinning reserve and optimizes operating costs [4][6]. A variety of methods for predicting wind speed and power have been documented in recent research [3].

The stochastic and intermittent nature of wind power generation creates obstacles to its widespread adoption [7]. Uncertainties associated with wind can impact system reliability, power quality, and raise concerns about integrating wind power into the grid, including issues related to balancing, management, and reserve capacities [7]. There is a non-linear correlation between wind speed and the electric power generated by the turbine which has an impact on errors in wind-driven systems [1]. Despite this, wind energy has expanded quickly and is advancing toward becoming a major worldwide energy source. Therefore, for maximizing the use of wind energy and seamlessly integrating wind power into the power system, precise wind speed prediction utilizing machine learning techniques is essential [8][9]. The goal of this study is to forecast wind speed using several machine learning algorithms, assess the effectiveness of those forecasts using metric parameters, and determine the best reliable model for wind speed prediction.

II. RELATED WORKS

In [2], a study was conducted to evaluate the effectiveness of SVM and MLP models for wind speed prediction. It employed a 12-year wind speed dataset (1970-1982), which underwent normalization between 0 and 1 to enhance performance. This study aims to predict the wind speed the next day from the current wind speed data. Various system orders ranging from 1 to 11 were examined. The findings revealed that, across all system orders, the SVM model, utilizing the Gaussian kernel, outperformed the MLP model, which employed the Levenberg-Marquardt optimization method and backpropagation algorithm. The SVM model exhibited superior trend fitting and achieved a lower mean squared error (MSE) and came to the conclusion that the SVM model was a better predictor. Furthermore, it was noted that the computational complexity associated with the SVM model was primarily present during the training phase, rendering it comparable to classical methods during the prediction process.

In [10], researchers investigated the potential of ANNs for wind speed prediction by utilizing data from multiple measuring stations in Turkey. The data was partitioned into two sections based on correlation coefficients among the stations. Notably, the ANN method demonstrated promising results in predicting wind speed, even in the absence of topographical or meteorological data. Instead, it leveraged data from references for calculating wind speed at the target station. The study suggested that selecting measuring stations with higher correlation factors could enhance the accuracy of the ANN method. This approach holds significant potential for wind speed prediction and can be extended to address similar forecasting challenges.

In [11], a Multi-Agent System (MAS) was introduced as a wind speed prediction tool. The MAS incorporated multiple regression algorithms, such as MLP, RBF, MLR, and SVM, to enhance prediction accuracy. To evaluate the effectiveness of the MAS method, ten years of real data from seven locations in Algeria were utilized. The study employed three fusion strategies to combine the individual models. The results indicated that this approach has the potential to surpass traditional prediction methods, showcasing its relevance in various forecasting problems beyond wind speed prediction. These applications include wind power forecasting and time series forecasting.

In [12], a hybrid approach was proposed and evaluated to tackle the challenge of accurate prediction, which is crucial for effective wind farm management and electricity generation from wind energy. Utilizing actual wind speed statistics from China, the model's accuracy was assessed. Notably, the hybrid model demonstrated outstanding performance in comparison to other prediction models, achieving MAPE values of 12% and 16% for the two datasets. This level of accuracy surpasses the existing range of 25-40%. However, it is important to acknowledge that the applicability of the model is limited to short-term wind speed patterns. To further enhance its practicality, future research could concentrate on developing a hybrid model that integrates additional prediction tools specifically designed for monthly or quarterly wind speed prediction. Such advancements would provide significant benefits in estimating power output and facilitating electricity market trading

In [13], a study evaluates and compares the effectiveness of different techniques for wind speed prediction. Four statistical methods are assessed in terms of their predictive power. The results indicate that the extrapolation technique with periodic curve fitting and the use of ANN demonstrate effectiveness in predicting wind speed. Conversely, the remaining two methods exhibit lower effectiveness. To assess the prediction accuracy of each method, the study employs the RMSE, with the extrapolation technique with periodic curve fitting yielding the lowest RMSE. However, it is acknowledged in the article that wind speed prediction can be complicated by various factors, making it challenging to select an appropriate regression model and achieve an effective fit.

In [14], the study aimed to develop an ANN model specifically for prediction in Himachal Pradesh, India. They presented the predicted wind speeds for 11 different locations, with wind power outputs enabling them to be used for tiny lighting applications. A sensitivity test was done to assess the model's accuracy and find the right number of hidden layer neurons. This analysis led to the establishment of an MLP neural network structure of 6-25-1, which demonstrated the lowest MAPE. An R-value of 0.98, which was highlighted in the study, showed that the constructed ANN model was highly accurate in forecasting wind speeds. Furthermore, a comparison between wind speeds measured by NASA and ground-based measurements highlighted the accuracy of the latter in wind resource assessment.

In [15], accurate speed forecasting, which is essential for managing wind farms effectively and producing renewable energy, was the subject of research. The study suggested a hybrid model that incorporates the EWT, CSA, and Least Squares LSSVM approaches to handle the volatility and autocorrelation in wind speed data. The EWT method was employed to eliminate stochastic volatility and extract precise wind speed information. The LSSVM algorithm served as the predictor, with CSA optimization of its parameters for accurate wind speed forecasts. The hybrid model was assessed demonstrating superior forecasting capability compared to existing models. The study also examined the impact of the LSSVM kernel function on prediction accuracy, suggesting potential for further improvement. This hybrid approach holds promise for enhancing speed prediction, and supporting renewable energy production and management.

In [16], SOM and a network technique are used in a study to propose a hybrid computing model that will improve the accuracy of wind speed forecast in renewable energy systems. The effectiveness of the proposed model is assessed using real-time wind data and compared to conventional models. The results show that the hybrid model performs better than the traditional models, with a reduced RMSE of 0.0828. This proves its capacity to considerably raise the convergence rate and forecast quality of wind speed. The study recommends that the hybrid model holds the potential for advancing renewable energy systems. Moreover, it recommends that future research should focus on further enhancing the model's performance and exploring its potential applications in the field.

In [17], The study develops a hybrid wind speed forecasting model called SARIMAeLSSVM. By combining SARIMA and LSSVM techniques, the proposed model aims to achieve higher prediction accuracy compared to conventional models. Using monthly wind speed data collected from two locations, the performance of the SARIMAeLSSVM model is assessed and contrasted with that of other models already in use. The study's conclusions show that the SARIMAeLSSVM model works better than all other models, leading to considerable decreases in three statistical errors.The model's performance is further validated through a hypothesis test with a 90% confidence level. Notably, the proposed hybrid model is characterized by its simplicity, computational efficiency, and the requirement of only a small amount of data for error correction. The study's findings could benefit wind farm operations and initiatives, and the created SARIMAeLSSVM model could be a useful tool for enhancing monthly wind speed prediction.

In [18], The hyper-parameter estimation problem is addressed in the research together with the enhancement of SVMr for wind speed prediction in a Spanish wind farm. The work uses EP and PSO algorithms to optimize the SVMr model in order to get around this problem. The performance of the optimized model is compared to that of MLP models, with MAE used as the performance metric. The findings reveal that the proposed evolutionary SVMr system outperforms the MLP models, showcasing the effectiveness of employing evolutionary computation techniques for hyperparameter estimation. The study offers advantages to researchers working in this particular field and delivers insightful information on how these strategies are applied for wind turbine wind speed prediction.

In [19], the study compares the performance of six machine learning models for short-term wind speed prediction using data collected from five stations in Tamil Nadu, India. These models are assessed based on a variety of performance metrics. The findings of the study reveal that LDMR demonstrates the highest prediction accuracy among the evaluated models. On the other hand, ELM stands out as the most computationally efficient model. Consequently, LDMR could serve as a benchmark for short-term wind speed prediction due to its superior generalization performance. The study emphasizes the importance of exploring computationally less expensive least squares-based models, such as LDMR, in wind speed prediction and other hydrological applications. This approach helps to reduce computational costs while still maintaining high generalization performance.

III. Research Methods

A. Dataset

The data used in the study was obtained from a publicly available dataset in the Philippines, specifically from PAGASA. The dataset covered daily observations spanning from the year 2000 to 2022. The data was collected on a daily basis, providing a comprehensive overview of the climate patterns over the years. The dataset served as a reliable and credible information source for the research, allowing for accurate analysis and interpretation of the trends and patterns observed over the years. The utilization of this dataset allowed for an in-depth exploration of the climate patterns in the Philippines over the past two decades.

B. Data Preprocessing

1) Data Cleaning: The pre-processing steps for the data involved removing missing values through the removal method. Outliers were cleaned by removing them using a moving median detection method, where a threshold factor of 3 was used. The moving window type was centered and had a window length of 3. The data were normalized using the z-score method, with the standard deviation as the z-score type. Lastly, smoothing was applied using the moving mean method, where the smoothing parameter was defined by the smoothing factor, which was set to 1.

2) Feature Selection: The dataset contains 9 features- evaporation, pressure, cloud cover, wind direction, maximum temperature, minimum temperature, mean temperature, relative humidity, rainfall, and 1 target variable which is wind speed.

3) Validation Scheme and Data Splitting: To ensure that the model's performance was accurate and reliable, a 10-fold cross-validation scheme was implemented. This involved splitting the dataset into ten equal parts, with nine of them being utilized for training the model and one left for testing its performance. This process was repeated ten times, with each of the ten parts used as the testing set once. In addition, the data was split into an 80:20 ratio for training and testing, respectively. This enabled the model to be trained on a significant portion of the data, while still retaining enough data to test its performance. The combination of these validation and splitting methods allowed for a thorough evaluation of the model's performance, ensuring its accuracy and reliability in predicting outcomes.

C. Training and Testing

The research involved the process of training and testing a model to analyze and predict outcomes. The training process involved using a significant portion of the available data to train the model, and the testing process involved evaluating the model's performance on the remaining data.

D. Hyperparameter Tuning

The research included the process of hyperparameter tuning to optimize performance. Hyperparameter tuning is a vital step in machine learning where the parameters of the model are adjusted to achieve the best possible outcomes. In this study, the model's hyperparameters were systematically varied and assessed to identify the optimal settings for optimal performance. This process involved testing different values for each hyperparameter and evaluating the corresponding impact on the model's performance. This process helped to ensure that the model's performance was optimized for the specific task it was designed to perform and that the results obtained were as accurate and reliable as possible.

IV. Results and Discussion

Table I presents the results of various machine learning models. The Matern 5/2 GPR model demonstrated the highest R-Squared value and the lowest RMSE, indicating its superior performance among other models, followed by ensemble methods like bagged trees. On the other hand, some of the SVM models and linear regression demonstrated lower performance compared to other models. These findings underscore the importance of carefully selecting the appropriate model for a particular dataset and problem, as this can significantly impact the model's accuracy and performance. Results obtained without hyperparameter tuning.

TABLE I. SUMMARY OF MACHINE LEARNING REGRESSION MODEL RESULTS

Model	10 cross-fold validation, 80:20 train-test ratio			
	RMSE	*Rsquared*	*MSE*	*MAE*
Linear Regression (Linear)	0.01064	0.979915	0.000113	0.007812
Linear Regression (Interactions Linear)	0.004758	0.995983	2.26E-05	0.003813
Linear Regression (Robust Linear)	0.011265	0.977482	0.000127	0.007544
Stepwise Linear Regression	0.00478	0.995946	2.28E-05	0.003808
Tree (Fine Tree)	0.002444	0.99894	5.98E-06	0.001422
Tree (Medium Tree)	0.003552	0.997761	1.26E-05	0.002278
Tree (Coarse Tree)	0.008545	0.987045	7.30E-05	0.006394
SVM (Linear SVM)	0.012733	0.971232	0.000162	0.00981
SVM (Quadratic SVM)	0.006721	0.991986	4.52E-05	0.005833
SVM (Cubic SVM)	0.006596	0.992282	4.35E-05	0.005687
SVM (Fine Gaussian SVM)	0.007685	0.989522	5.91E-05	0.006984
SVM (Medium Gaussian SVM)	0.006258	0.99305	3.92E-05	0.005298
SVM (Coarse Gaussian SVM)	0.012359	0.972896	0.000153	0.009766
Ensemble (Boosted Trees)	0.006015	0.99358	3.62E-05	0.004654
Ensemble (Bagged Trees)	0.002455	0.998931	6.03E-06	0.001748
Gaussian Process Regression (Squared Exponential GPR)	0.000885	0.999861	7.84E-07	0.000672
Gaussian Process Regression (Matern 5/2 GPR)	0.00084	0.999875	7.06E-07	0.000626
Gaussian Process Regression (Exponential GPR)	0.000951	0.999839	9.05E-07	0.000657
Gaussian Process Regression (Rational Quadtraic GPR)	0.000852	0.999871	7.26E-07	0.00063
Neural Network (Narrow Neural Network)	0.004359	0.996629	1.90E-05	0.003239
Neural Network (Medium Neural Network)	0.004816	0.995885	2.32E-05	0.00346
Neural Network (Wide Neural Network)	0.001763	0.999449	3.11E-06	0.001289
Neural Network (Bilayered Neural Network0	0.002671	0.998734	7.13E-06	0.001891
Neural Network (Trilayered Neural Network)	0.002702	0.998705	7.30E-06	0.00207
Kernel (SVM Kernel)	0.006625	0.992212	4.39E-05	0.005329
Kernel (Least Squares Regression Kernel)	0.008492	0.987206	7.21E-05	0.006377

The impact of data cleaning becomes evident when comparing the performance of the models with and without it, as illustrated in Tables II and III. The "without data cleaning" table shows relatively higher RMSE values, indicating larger prediction errors, while the R-squared values are lower, suggesting a weaker model fit. However, the models demonstrate significantly improved performance in the "with data cleaning" table. The RMSE values decrease substantially, reflecting reduced prediction errors, and the R-squared values approach 1, indicating a closer fit to the data. These improvements highlight the effectiveness of preprocessing techniques in enhancing model accuracy and reliability. By addressing data inconsistencies, handling missing values, and applying feature scaling, preprocessing enables the models to better capture patterns and relationships in the data, resulting in more robust and precise predictions.

Based on the evaluation of various machine learning models with hyperparameter tuning, as presented in Table III, it is clear that Gaussian Process Regression outperforms the other models in terms of RMSE, MSE, MAE, and R-squared values, with the lowest RMSE (0.000839996), MSE (7.06E-07), and MAE (0.000632566), and the highest R-squared value (0.999874806). Although the remaining models show varying performances, the SVM model ranks second with an RMSE of 0.001788057, while the Neural Network model performs the poorest with the highest RMSE of 0.003977832. These results emphasize the importance of selecting an appropriate model for wind speed prediction, as the choice of model can significantly affect the accuracy of predictions and overall model performance.

TABLE II. SUMMARY OF OPTIMIZED VALUES WITHOUT PRE-PROCESSING

Model	10 cross-fold validation, 80:20 train-test ratio			
	RMSE	*Rsquared*	*MSE*	*MAE*
Tree	0.88922	0.160376	0.790713	0.703298
Support Vector Machine	0.883424	0.171287	0.780437	0.678056
Gaussian Process Regression	0.804116	0.3134	0.646603	0.629434
Ensemble	0.81863	0.288391	0.670154	0.646889
Neural Network	0.971915	-0.00305	0.944618	0.724696

TABLE III. SUMMARY OF OPTIMIZED VALUES WITH PRE-PROCESSING

Model	10 cross-fold validation, 80:20 train-test ratio			
	RMSE	*Rsquared*	*MSE*	*MAE*
Tree	0.001847	0.999395	3.41E-06	0.001245
Support Vector Machine	0.001788	0.999433	3.20E-06	0.001227
Gaussian Process Regression	0.00084	0.999875	7.06E-07	0.000633
Ensemble	0.003473	0.99786	1.21E-05	0.002244
Neural Network	0.003978	0.997192	1.58E-05	0.002992

Table IV lists the pre-processed optimum hyperparameter values for the Gaussian Process Regression model that gave it the best performance. The model's predictions were more accurate to the hyperparameter adjustment.

TABLE IV. HYPERPARAMETER VALUES

Hyperparameter	Value
Sigma	0.0080
Basis function	Constant
Kernel function	Isotropic Matern 5/2
Kernel Scale	0.0034
Standardize data	false

The predicted versus actual plot for GPR is likely to show a tight cluster of points around the diagonal line, indicating that the predicted values are very close to the actual values. On the other hand, the plot for the Neural

Network model is likely to have a more scattered distribution of points, indicating that the predicted values are farther from the actual values. The remaining models, including Tree, SVM, and Ensemble, are likely to have varying degrees of scatter in their predicted versus actual plots, reflecting their respective levels of accuracy. The plot is an effective visual tool for evaluating the effectiveness of regression models and gaining an understanding of the nature of the relationship between the predictor and response variables.

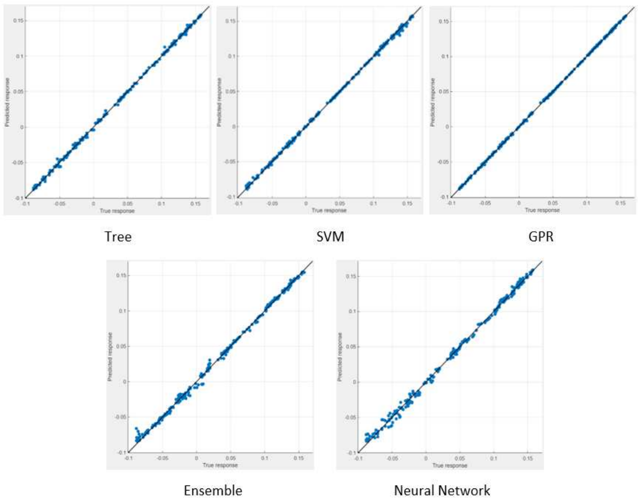

Fig. 1. Predicted versus Actual Plots

V. CONCLUSION

This study focused on predicting wind speed using a dataset spanning from 2000 to 2022, comprising nine features and daily observations. The data underwent quality-focused pre-processing, and machine learning models were trained and evaluated with hyperparameter tuning for optimal performance. Through a comparison of different metrics, Gaussian Process Regression (GPR) emerged as the top-performing model, demonstrating the lowest RMSE and highest R-squared value. The study emphasizes the significance of choosing a suitable machine learning model and optimizing its hyperparameters to improve wind speed forecast accuracy. It also emphasizes the significance of thorough data pre-processing to ensure the reliability and quality of the dataset. The superiority of GPR in wind speed prediction provides theoretical advantages, such as capturing complex relationships and non-linearities in wind data, leading to more accurate forecasts. From a practical perspective, GPR's superior performance offers benefits such as improved system safety, efficient dispatch, cost savings, and enhanced operational planning for wind farms and power utilities. Additionally, accurate wind speed prediction using GPR aids in load forecasting and optimal scheduling, contributing to a reliable and seamlessly integrated wind power system.

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