© August 2025| IJIRT | Volume 12 Issue 3 | ISSN: 2349-6002

Forecasting of Wind Energy Resources using Support Vector Machine

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Abstract—**The depletion of conventional fossil fuels, driven by the growing global population, underscores the need for alternative energy sources. Renewable energies, particularly wind, have proven to be viable substitutes that can meet global energy demands while preserving the environment. Accurate forecasting of wind energy resources is crucial for their optimal utilization, with various methods applied to achieve this. Among these, the support vector machine (SVM) modelling approach has demonstrated superior prediction performance, offering speed, simplicity, reliability, and accuracy. Critical analysis reveals that hybrid SVM models can achieve even higher accuracy for predicting wind energy across different locations. This investigation identifies key challenges and opportunities in this field and proposes novel hybrid models for future research to enhance the precision of wind energy predictions.**

Index Terms—**Artificial Neural Network, Forecasting, Support Vector Machine, Wind Energy.**

I. INTRODUCTION

The increasing reliance on renewable energy sources, such as wind energy, has driven the need for accurate forecasting models to manage energy production and integration into power grids. Wind energy are inherently variable, making it challenging to predict their availability and reliability. Traditional forecasting methods often struggle with this variability due to the non-linear and complex nature of weather patterns influencing these resources. Support Vector Machine (SVM) models, a type of machine learning algorithm, have emerged as a powerful tool for forecasting in various fields due to their ability to handle non-linear data and provide robust predictions. SVM models work by finding the optimal hyperplane that separates data into different classes, making them particularly effective in predicting outcomes based on historical data. When applied to wind energy forecasting, SVM models can analyzed historical weather data, including temperature, wind speed, and other relevant parameters, to accurately predict future energy outputs. The application of SVM models for forecasting wind energy resources addresses the critical need for precise predictions to enhance energy management and grid stability. By improving the accuracy of forecasts, these models help in optimizing energy production, reducing the reliance on fossil fuels, and supporting the integration of renewable energy into the power grid. This innovation is particularly significant in the context of increasing renewable energy adoption, where reliable and efficient forecasting is essential for ensuring a sustainable and stable energy supply. The present work focuses on applying Support Vector Machine (SVM) models for accurately forecasting wind energy resources, which are critical for the efficient use of renewable energy. As conventional fossil fuels continue to deplete, there is an increasing need for reliable alternative energy sources like wind energy. The invention addresses this need by leveraging SVM, a machine learning technique known for its high accuracy, simplicity, and reliability, to predict the availability and intensity of these renewable resources. The SVM models are designed to handle the complex, nonlinear relationships between various meteorological factors and energy output, making them particularly effective in forecasting wind energy. The invention also explores hybrid SVM models, which combine SVM with other predictive techniques to further enhance accuracy. These hybrid models are shown to outperform traditional methods in most scenarios, providing more precise forecasts that are essential for planning and optimizing the use of renewable energy resources. The invention identifies the main challenges in renewable energy forecasting and offers a solution that improves prediction accuracy, thereby supporting better integration of wind energy into the power grid. This advancement has the potential to significantly contribute to sustainable energy management.

II THE METHODOLOGY

Energy is crucial in modern society, and the growing demand and rapid industrialization are depleting conventional fossil fuels. Renewable energy sources, particularly wind and solar, have gained significant attention due to their abundance and sustainability. Over recent decades, a substantial number of wind turbines and photovoltaic cells have been installed globally. However, challenges persist, such as the variability in power generation due to fluctuations in wind speed, direction, and factors affecting solar energy, like solar elevation angle, haze, and cloud cover. These fluctuations can negatively impact the electrical grid and hinder the widespread adoption of renewable energy. Therefore, accurate forecasting of wind and solar energy output has become essential for effective generation and implementation. Traditional empirical models have been used to forecast wind and solar energy but have shown limitations in accuracy. Fortunately, artificial intelligence (AI) techniques have addressed these challenges effectively. AI methodologies, though relatively new, have shown promising results in system modelling and analysis across various scientific fields, offering 20 robust, fast, and accurate predictions. Among these AI models, Artificial Neural Networks (ANNs) have been widely applied for forecasting but have some limitations, such as incorrect predictions and time consumption for large networks. Additionally, there is no definitive method for selecting the optimal number of hidden layers or activation functions to create a high-precision model.

An alternative AI approach, the Support Vector Machine (SVM), has demonstrated better accuracy and speed in solving nonlinear problems. This paper critically reviews the application of SVM models for forecasting wind and solar energy. It aims to fill a gap in the literature by providing a comprehensive analysis of SVM applications in these fields. Distribution of Publications Over Time The growing interest in accurately predicting wind and solar energy resources has led to the widespread adoption of Support Vector Machines (SVMs), which have seen significant acceptance since 2009 (Fig. 1). A comprehensive selection process identified 75 publications focusing on SVM methodologies. This surge in interest can be attributed to recent advancements in the development of SVM techniques. While SVM applications in wind energy estimation are relatively new, the global academic community is increasingly turning its attention to this area. A notable peak in publications occurred between 2015 and 2017, with 47 articles published during this period. The rising number of studies highlights the effectiveness of intelligent models like SVMs in providing fast and accurate results, aligning with the growing focus on optimizing renewable energy resource utilization.

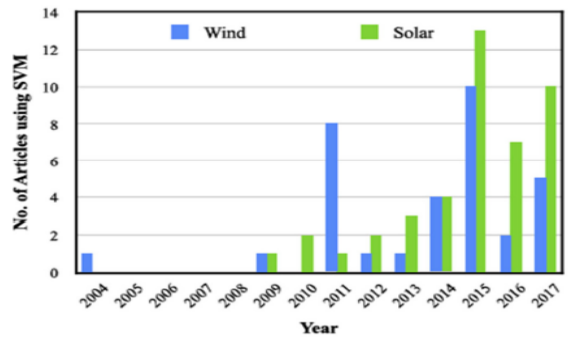

Fig.1 Trend in the Number of Publications Using SVMs over the Years

The distribution of publications across various subject areas within wind energy research are presented in Fig 2. The 75 collected articles were categorized based on their specific research focus. The data clearly shows that SVMs are applied in diverse contexts and perspectives within the field of renewable energy. For solar energy, out of 42 articles, the majority (50%) focus on the application of SVMs for solar radiation prediction. Other areas include SVMs applied to solar collectors and photovoltaic systems (24%) and solar irradiation (21%). Conversely, research on solar air heater systems (2%) and solar insolation (2%) using SVMs is less common. In wind energy research, which comprises 35 articles, the predominant focus is on forecasting wind speed (69%), followed by wind power prediction (29%). However, the application of SVMs to predict wind direction (3%) is less frequently explored.

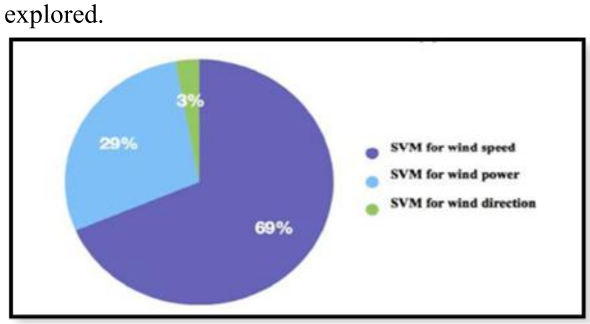

Fig. 2 Distribution of Publications across Subject Areas for Wind Energy

III. SVM MODELLING APPROACH

Support Vector Machines (SVMs), rooted in statistical learning theory and the principle of structural risk minimization, and were first introduced by Cortes and Vapnik in 1995. The SVM network structure is illustrated in Fig. 3. SVMs have been successfully employed for various tasks, including image retrieval, fault diagnosis, text detection, and regression analysis.

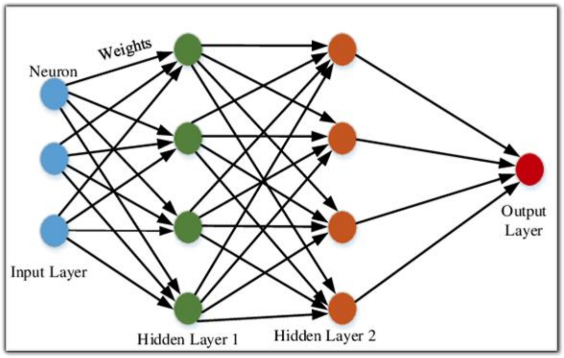

Fig. 3 SVM Network Structure

The core idea of SVMs involves transforming nonlinear input data into a high-dimensional feature space, where a hyperplane can be identified using nonlinear mapping. This method is highly effective in classification, pattern recognition, and regression tasks, often outperforming traditional statistical models. Support Vector Regression (SVR), a variant of SVM, is particularly useful for function approximation and regression. SVM models employ various kernel functions, such as polynomial (Poly), exponential radial basis function (ERBF), radial basis function (RBF), sigmoid, and linear functions. A training dataset of input-output pairs, denoted as $Z = \{c_{i,}g_i \mid i = 1,2,3, \ldots \ldots, n\}$, where c_i a q-dimensional is input vector and g_i is the corresponding target value, is used to construct the regression model (Equation 1):

$$g = u^T \varphi(c) + b \qquad (1)$$

Here, u represents the weight vector, b is the bias term, and φ(c) denotes a nonlinear mapping function that projects c into a higher-dimensional feature space. To obtain u, the following regularized function (Equation 2) is minimized under the constraints of Equations 3:

$$min \frac{1}{2} \|u\|^2 + C \sum_{i=1}^{N} (\xi_i + \xi_i^*) \qquad (2)$$

Where ξ_i and ξ_i^* are positive slack variables, and C is a penalty parameter balancing regularization and empirical risk. The SVR solution involves introducing Lagrange multipliers, resulting in the following expression (Equation 3):

$$f(c) = \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) K(c, c_i) + b \qquad (3)$$

The key characteristics of the SVM approach include:

1. High precision and robustness.
2. Capability to model complex nonlinear decision boundaries.
3. Reduced likelihood of overfitting compared to other models.
4. Compact representation of the learned model.
5. Versatility in applications such as pattern recognition, regression, and classification

In recent years, SVM approaches have been extensively applied in wind energy research, ranging from simple to hybrid and complex models. The Least Squares Support Vector Machine (LSSVM), introduced by Suykens and Vandewalle in 1999, extends the standard SVM by solving a set of linear equations instead of a convex quadratic programming problem, simplifying numerical implementation. The accuracy of SVM models heavily relies on the careful selection of parameters. Therefore, and cuckoo optimization algorithm (COA). These techniques enhance efficiency, accuracy, and computational speed in machine learning applications.

IV. RELATED WORK: WIND ENERGY PREDICTION

The development of Support Vector Machines (SVM) for wind energy, specifically in Predicting wind speed, has been extensively explored by various researchers. An SVM model developed to predict wind speed using a 12-year dataset from Madina, Saudi Arabia. The results in [1] demonstrated that the SVM model had a lower mean square error (MSE) compared to a multilayer perceptron (MLP) neural network, indicating higher precision [2] in **2008** extended SVM modelling to short term wind speed forecasting using a 10-year dataset measured every 10 minutes. The study highlighted that the performance of SVM varied with the type of kernel, Epsilon value, and number of inputs, and SVM outperformed ANN in terms of computational efficiency. The Least Squares SVM (LSSVM) used to estimate short-term wind speed in North Dakota [3]. By fine-tuning the model parameters using different kernel functions (linear, RBF, and Poly), they demonstrated the robustness of LSSVM models compared to a persistence model. New training structures based on Support Vector Regression (SVR) has been explored for wind speed prediction using data from five wind turbines in Spain [4]. Their model was more robust compared to MLP models, particularly in handling complex datasets. A further emphasis on evaluating different kernel functions and using Particle Swarm Optimization (PSO) for tuning parameters in SVM. They concluded that an RBF kernel function combined with PSO provided a prediction accuracy of 98.667%. The hybridized SVM with Evolutionary Programming (EP) and PSO has been studied [5] [6] to enhance the model's performance in estimating wind speed. The study used data from a wind farm in Spain, and the results showed that PSO and EP were effective in hyper parameter optimization. A GA-optimized LSSVM model to predict short-term wind speed in Taiwan [7]. The model achieved an average error of around 2.27%, and the authors suggested that including more influencing factors could improve accuracy further. The authors [8] combined SVM with the wavelet packet decomposition method for short-term wind speed prediction. The model showed good agreement with experimental data, than average absolute error (AAE) of 0.3235 m/s and an average relative error (ARE) of 5.49%.

A hybrid SARIMA-LSSVM model for mean monthly wind speed prediction was developed by [9] in China. This model outperformed single ARIMA, SARIMA, LSSVM, and ARIMA-SVM models in terms of efficiency and precision. The integrated multiple LSSVM models using fuzzy theory was studied for wind power prediction in China and found to be robust and reliable [10]. Hu et al. proposed an EEMD-SVM hybrid model for wind speed forecasting, demonstrating that it outperformed [11] other models, including ARIMA, SARIMA, and EMD-SVM, in terms of accuracy and consistency. The SVR-UKF approach, combining SVR with the Unscented Kalman Filter (UKF) to predict short-term wind speed was introduced [12]. The model was tested on data from Massachusetts and showed better accuracy than ANN and other traditional approaches. [13][14] Enhances wind speed forecasting accuracy using SVM-based hybrid models. [13 integrated Support Vector Machines with Wavelet Transform and Genetic Algorithms, achieving strong performance on MAE, MAPE, and RMSE. [14] combines SVM with Grey theory, improving MAPE and MSE in U.S.-based predictions. [15] Has combined ARIMA, ELM, SVM, and LSSVM for short-term wind speed prediction. The model performed well compared to traditional methods. A reduced SVM (RSVM) introduces [16] optimized by PSO for wind speed forecasting, demonstrating superior performance in computational time and accuracy compared to traditional SVM.Also an hybrid model combining C-LSSVM with PSOGSA for wind speed prediction, showing significant improvements in [17] forecasting accuracy on daily and 10-minute scales. Hu et al. in 2015 proposed a EWT-CSA-LSSVM hybrid model for one-step ahead and multi-step-ahead wind speed prediction, which outperformed other models [18] in Hebei Province, China. A hybrid SVR model optimized by GA, PSO, and COA for wind speed prediction in China, with COA-SVR showing [19] robustness in multi-step-ahead predictions. A hybrid model using fast ensemble empirical mode decomposition (FEEMD) and a bat algorithm with LSSVM [20] showing robustness in forecasting wind speed compared to other models.

V. RESULTS AND DISCUSSION

The Least Squares Support Vector Machine (LSSVM), known for its high generalization capability, not only leverages the strengths of Support Vector Machines (SVM) but also simplifies the problem by solving a set of linear equations instead of relying on complex quadratic programming. This makes LSSVM a promising approach in research, deserving of further investigation due to its potential benefits. There are many unexplored opportunities to enhance forecasting models by leveraging this approach. Additionally, the precise selection of SVM parameters significantly impacts model accuracy. Traditional methods like gradient descent and grid search, while commonly used, may not be the best choices due to their computational complexity. Particle Swarm Optimization (PSO) and Harmony Search (HS) algorithms have also shown limitations, such as slow convergence. A combination of LSSVM with Genetic Algorithms (GA) has been successfully applied in fields like chemical processing and air-conditioning, demonstrating its effectiveness. The performance of the Bat Algorithm (BA) for optimizing parameters is noteworthy as well, offering excellent results. Moreover, combining LSSVM with the Firefly Algorithm (FFA) is recommended for further research, given FFA's advantages in solving optimization problems.

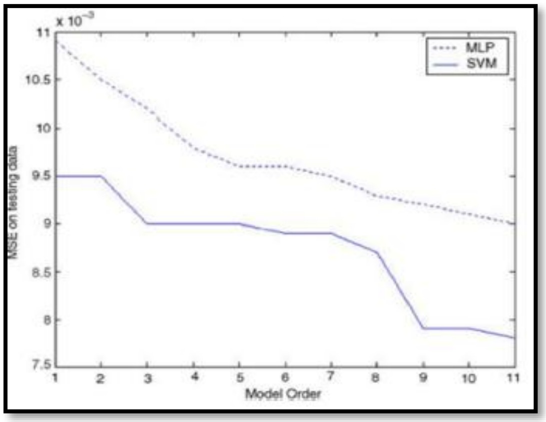

Fig. 4 Comparison between the MSE of SVM and MLP on testing data

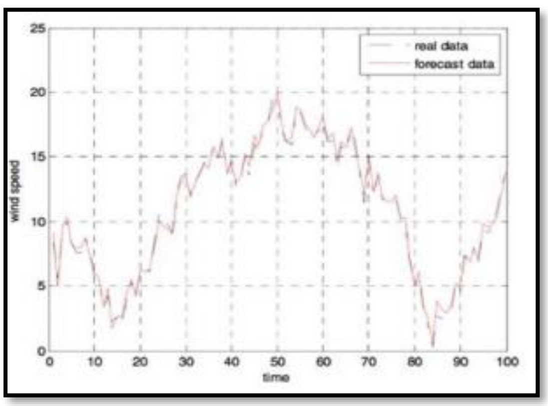

Fig. 5 Result of the short-term wind speed prediction

Furthermore, the Wavelet Transform (WT) algorithm, commonly used for multi-resolution data processing of non-stationary input signals, could be replaced by the Fast Ensemble Empirical Mode Decomposition (FEEMD) algorithm. Proposed in 2014, FEEMD has shown significant improvements in real-time computational performance. Lastly, experimental data often contain uncertainties that can reduce model accuracy. Outlier detection is essential to evaluate data samples and identify those that deviate significantly from the rest. Outliers can arise from various sources, such as changes in system behaviour, mechanical faults, instrument errors, or human errors, and they can negatively impact the predictive ability of a model. Employing mathematical approaches to detect and address these outliers can greatly enhance the efficiency and reliability of the model.

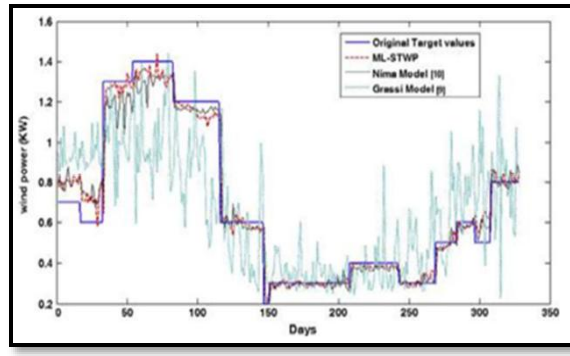

Fig. 6 Comparison of wind power prediction by various models

VI. CONCLUSION

Support Vector Machine (SVM) models are being used for forecasting wind energy resources due to the variability of these resources across different locations. SVM is particularly effective in short-term energy forecasting due to its ability to handle non-linear data patterns and its robust prediction accuracy. However, the performance of SVM models depends on the choice of hyper parameters, which can be optimized for high accuracy. Integrating SVM with other models can enhance prediction precision, but may suffer from slower response times due to increased complexity. Current research aims to develop hybrid models that combine SVM's strengths with other techniques to improve the speed, accuracy, and adaptability of energy forecasting methods.

REFERENCE

[1] M.A. Mohandes, T.O. Halawani, S. Rehman, Ahmed A. Hussain - Support vector machines for wind speed prediction, Renewable Energy, 29(6), pp. 939-947, 2004.

[2] Sreelakshmi, K. & P., Ramakanth - Short term wind speed prediction using support vector machine model. WSEAS Transactions on Computers. Volume 7. pp 1828-1837, 2008.

[3] Junyi Zhou, Jing Shi, Gong Li - Fine tuning support vector machines for short-term wind speed forecasting, Energy Conversion and Management, 52(4), pp 1990-1998,2011

[4] Santamaria-Bonfil, Guillermo & Reyes Ballesteros, Alberto & Gershenson, Carlos - Wind Speed Forecasting For Wind Farms: A Method Based on Support Vector Regression. Renewable Energy. Volume 85. Pages 790-809, 2015.

[5] Lianghai, Wu & Yiming, Chen - Study of prediction based on RBF Neural network optimized by PSO, ICCET 2010 - 2010 International Conference on Computer Engineering and Technology, Proceedings. Volume 6, 2010.

[6] Salcedo-Sanz, Sancho & Ortiz-García, Emilio & Pérez-Bellido, Ángel & Portilla-Figueras, Antonio & Prieto, Luis - Short term wind speed prediction based on evolutionary support vector regression algorithms, Expert Syst and Appl. Volume 38. pp 4052-4057, 2011

[7] Chi-Yo Huang, Bo-Yu Chiang, Shih-Yu Chang, Gwo-Hshiung Tzeng & Chun-Chieh Tseng, Predicting of the Short Term Wind Speed by Using a Real Valued Genetic Algorithm Based Least Squared Support Vector Machine, Intelligent Decision Technologies. Smart Innovation, Systems and Technologies, Volume 10, pp 567–575, 2011

[8] Zeng, D., Liu, Y., Liu, J., Liu, J - Short-Term Wind Speed Forecast Based on Best Wavelet Tree Decomposition and Support Vector Machine Regression, Advances in Automation and Robotics, Volume 2. Lecture Notes in Electrical Engineering, vol 123, pp 373–379. 2011

[9] Guo, Zhenhai & Zhao, Bennett & Zhang, Wenyu & Wang, Jianzhou - A corrected hybrid approach for wind speed prediction in Hexi Corridor of China",. Fuel and Energy Abstracts. Volume 36. pp 1668-1679, 2011

[10] Zhang, Q., Lai, K. K., Niu, D., Wang, Q., & Zhang, X - A Fuzzy Group Forecasting Model Based on Least Squares Support Vector Machine (LS-SVM) for Short-Term Wind Power.", Energies, 5(9), pp 3329-3346. 2012

[11] Hu, J., Wang, J., & Zeng, G - A hybrid forecasting approach applied to wind speed time series", Renewable Energy, Volume 60, pp 185-194. 2013

[12] Chen, Kuilin & yu, Jie - Short-term wind speed prediction using an unscented Kalman filter based state-space support vector regression approach." Applied Energy, Volume 113. pp 690-705.2014.

[13] Liu, Da & Niu, Dongxiao & Wang, Hui & Fan, Leilei. - Short-term wind speed forecasting using wavelet transform and support vector machines optimized by genetic algorithm. Renewable Energy. 62. pp. 592-597, 2014.

[14] Xiao, Yancai - Wind Power Prediction Based on Improved Grey Theory and SVM. Journal of Information and Computational Science. Volume 11. pp. 5937-5944, 2014.

[15] Yun Wang, Jianzhou Wang, Xiang Wei - A hybrid wind speed forecasting model based on phase space reconstruction theory and Markov model: A case study of wind farms in northwest China, journal of Energy (sciencedirect), Volume 91, pp 556-572, 2015.

[16] Kong, Xiaobing & Liu, Xiangjie & Shi, Ruifeng & Lee, Kwang - Wind speed prediction using reduced support vector machines with feature selection, Neurocomputing. Volume 169. 2015

[17] Jiang, Ping & Wang, Yun & Wang, Jianzhou - Short-term wind speed forecasting using a hybrid model. Energy. Volume 119. 2016

[18] Jianming Hu, Jianzhou Wang, Kailiang Ma - A hybrid technique for short-term wind speed prediction, Journal of Energy (sciencedirect), Volume 81, pp 563-574, 2015.

[19] Jianzhou Wang, Qingping Zhou, Haiyan Jiang, and Ru Hou - Short-Term Wind Speed Forecasting Using Support Vector Regression Optimized by Cuckoo Optimization Algorithm, Mathematical Problems in Engineering, Volume 2015, pp 1-13, 2015.

[20] Wei Sun & Mohan Liu & Yi Liang - Wind Speed Forecasting Based on FEEMD and LSSVM Optimized by the Bat Algorithm, Energies, MDPI, 8(7), pp 1-23, June 2015.