Development of an AI-Based Model with Low Computational Complexity for Accurate Wind Energy Forecasting

Shiwantha Dilshan,Nimesh Fernando
Wayamba University of Sri Lanka
shiwanthawyb@icloud.com, nimeshaf@wyb.ac.lk

ABSTRACT

Most countries primarily relay on fossil fuel for electricity generation, leading to fossil fuel depletion and environmental pollution. The countries are developed technologies for renewable energy generation. The wind energy being promoted as a superior renewable energy. However, wind energy has its challengers, particularly uncertainty that can affect overall system stability. The accurate short-term forecasting of wind energy was crucial for ensuring grid stability. Both physical and AI-based models can effectively be utilized for wind energy prediction. AI-based methodologies have shown superior effectiveness, efficiency, and accuracy when compared to traditional physical models. The lightweight AI-based forecasting model was particularly significant for processing devices, enabling faster computations and substantially more cost-effective forecasting. The research utilized simulation software to develop an Artificial Neural Network (ANN) model, initially incorporating eight meteorological parameters. Four of these parameters showed weak correlations and were subsequently removed from the model. Further optimization was achieved through pruning and quantization techniques, significantly reducing computational complexity. The optimized model demonstrates a notable reduction in both training time by 92.69% and inference time by 63.83%, while maintaining accuracy with only a marginal decrease of 3.99% compared to the initial model. These improvements were achieved with minimal loss in predictive accuracy, significantly reducing computational complexity. The study concludes that the optimized ANN model is well-suited for real-time wind power forecasting, offering a balance between accuracy and computational efficiency. This approach not only facilitates better grid management but also extends the applicability of AI-based forecasting to devices with limited processing capabilities. Future work could explore additional complexity reduction techniques and broader deployment scenarios.

KEYWORDS: *Wind forecasting, artificial intelligence, computational efficiency, model optimization, simulation, time-series prediction*

INTRODUCTION

Most countries primarily rely on fossil fuels for electricity generation, leading to fossil fuel depletion and environmental pollution (Li et al., 2019). Wind energy is being promoted as a superior renewable resource compared to tidal energy. In 2020, wind turbines contributed 8.4% of the total utility-scale electricity generation in the United States, with projections indicating an increase to 20% by 2030 and 35% by 2050 (Alkesaiberi et al., 2022). However, wind power has its challenges, particularly uncertainties that can affect power quality, grid security, and overall system stability. Accurate and timely forecasting of wind power is crucial for the safe operation of the grid (Ju et al., 2019) and for balancing electricity supply and demand, thus ensuring grid stability.

The meteorological factors can change rapidly and unpredictability, leading to fluctuations in wind energy generation. This uncertainty was made it challenging to model because historical data may not fully capture future patten. Predicting wind energy involves dealing with uncertainty in meteorological conditions. Even with advanced forecasting techniques, there was always a margin of error due to unpredictability of weather. Reliable data on meteorological factors were crucial for accurate modeling. However, data may be sparse or of varying quality in some regions, affecting the reliability of models.

Both physical models and AI-based models can be effectively utilized for wind power prediction, each offering distinct advantages and challenges. Engaging qualified personnel in the calculations necessary for physical models is crucial, as their expertise directly impacts the reliability of the results. Furthermore, substantial effort is required for data collection, processing, and analysis to generate meaningful outputs. This reliance on traditional methods can often lead to delays in obtaining results, resulting in increased time consumption, higher costs, and potential reductions in accuracy. In contrast, AI-based methodologies have consistently demonstrated superior effectiveness, efficiency, and accuracy when compared to traditional physical models. The advancements in AI not only streamline the forecasting process but also enhance

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predictive capabilities. Moreover, various simulation software packages have emerged, enabling the development of AI models through straightforward procedures that are both cost-effective and user friendly. These software tools also incorporate features that provide accuracy metrics, allowing users to evaluate and refine model performance systematically.

A large amount of data was used to build an AI-based accurate wind power prediction model. Wind energy generation was influenced by various parameters, including wind speed, wind direction, air density, etc. A large number of datasets for each parameter were required to be input, which was the cause of increased computational complexity in the AI-based forecasting model, leading to longer processing times. Although modern computers were designed to be high-performance, this was not considered a significant problem. However, the types of processing devices available in the grids could not be determined. Therefore, it was deemed essential to reduce computational complexity to ensure compatibility with a broader range of processing devices, including those that were expected to have limited capabilities. The reduction in the AI model's computational complexity enables it to run on more cost-effective and lower-power processing devices, such as older computers used in wind farms.

The primary objective of this research is to develop and optimize an AI-based short-term forecasting model for wind power generation using simulation software. The study aims to reduce computational complexity while evaluating the performance improvements of the optimized model relative to the baseline version. This goal is achieved through the following three key objectives:

Development of an AI-based forecasting model for wind power generation.

Optimization of the model to minimize computational overhead.

Evaluation of the optimized model's performance by comparing key metrics with those of the initial model.

The paper was structured as follows: the literature review section examined existing studies on wind power forecasting, key parameters influencing wind energy, and techniques for reducing computational complexity. The methodology section detailed the processes of dataset preparation, model development, and optimization. The results and discussion section presented the performance of both the initial and optimized models. The conclusion summarized the study's findings and outlined directions for future research. Through this work, a contribution was made toward developing more efficient and scalable wind energy forecasting solutions, thereby supporting the broader adoption of renewable energy.

LITERATURE REVIEW

Wind energy forecasting has been extensively studied using various parameters and methodologies, as highlighted in recent research. A comparative analysis of these studies reveals the diversity of approaches and the critical parameters influencing wind power prediction. (Alkesaiberi et al., 2022) employed a comprehensive set of parameters, including weather conditions, turbine specifications (e.g., rotor features, gearbox ratios), ambient temperature, blade pitch angle, nacelle position, hub height, and wind characteristics (direction, speed, and intensity), alongside temporal and geographic factors. (Kosovic et al., 2020) expanded the scope by incorporating additional parameters like ice accumulation and horizontal grid spacing, emphasizing the importance of localized atmospheric conditions. (Tarek et al., 2023) focused on wind speed, wind direction, air density, active power, theoretical power, and time-series data, while (Lipu et al., 2021) and (Ju et al., 2019) utilized time-series wind power values to develop forecasting models. (Hu et al., 2021) integrated meteorological data, including wind speed, wind direction, air pressure, temperature, and relative humidity. (Pang et al., 2021) further extended the parameter set by including humidity, air pressure, air density, rainfall, and surface sensible heat, employing machine learning to analyze correlations. (Franke et al., 2021) highlighted the role of air density, rotor area, Betz coefficient, and hub height in wind power calculations. Similarly, (Badran & Abdulhadi, n.d.) examined turbinespecific parameters such as swept area, power coefficient, and air velocity, while (Van Der Merwe et al., n.d.) explored the interplay between wind speed, direction, air density, pressure, and temperature.

The forecasting of wind energy has garnered significant attention, leading to a variety of studies that leverage artificial intelligence (AI) models. These studies explore diverse parameters and employ different AI techniques to enhance the accuracy of wind energy predictions. One notable study (Alkesaiberi et al., 2022) compared multiple machines learning approaches, focusing on kernel-driven models such as Support Vector Regression (SVR) and Gaussian Process Regression (GPR), alongside ensemble learning models. The findings indicated that both GPR and ensemble models achieved satisfactory performance in predicting wind power. The parameters utilized in this research included weather conditions, turbine specifications (e.g., rotor features and gearbox ratios), ambient temperature, blade pitch angle, nacelle position, hub height, turbine operational status, and wind characteristics (direction, speed, and intensity), as well as temporal factors and geographic location.

Table 13. Summary of research and parameters

Research	Parameters	AI method
(Alkesaiberi, Harrou and Sun, 2022)	Weather, type of turbine, rotor features, ambient temperature, blade pitch angle, gearbox gear ratio, nacelle position, hub height, turbine status, location, time, wind direction, wind speed	Gaussian Process Regression
(Kosovic et al., 2020)	wind direction, wind speed, wind intensity hub-height, ice accreted, temperature weather condition (shout down), horizontal grid spacing, location, time	AI analog ensemble
(Tarek et al., 2023)	wind direction, wind speed, Air Density, Active Power, Theoretical Power, Date/Time	Deep Learning Models
(Lipu et al., 2021)	wind power values (Time series data)	Machine learning
(Ju et al., 2019)	wind power values (Time series data)	Machine learning
(Hu et al., 2021)	wind speed, wind direction, air pressure, temperature, relative humidity weather data at certain time intervals	Extreme Learning Machine
(Pang, Yu and Liu, 2021)	wind speed, wind direction, temperature humidity, air pressure, air density, rainfall Surface sensible heat	Deep belief network-based hybrid forecasting method
(Franke et al., 2021)	air density, rotor area, Betz coefficient rated wind speed per time interval, hub height	
(Badran and Abdulhadi, no date)	wind speed, air density, temperature, air, pressure, area swept, hub height	
(Van Der Merwe et al., no date)	wind speed, wind direction, air density, air pressure, air temperature, area, power coefficient	

Another study (Kosovic et al., 2020) expanded on this by incorporating additional parameters such as ice accumulation and horizontal grid spacing, emphasizing the importance of localized atmospheric conditions. (Kosovic et al., 2020) also discussed existing forecasting methodologies, including the DICast forecasting system for weather predictions and various numerical weather prediction (NWP) models, such as the Weather Research and Forecasting model with Real-Time FourDimensional Data Assimilation (WRF RTFDDA). These methodologies leverage mathematical models to analyze atmospheric data, facilitating improved input forecasting for AI models. Furthermore, a comparative analysis of forecasting techniques was conducted in the study (Qureshi et al., 2023) This research evaluated the accuracy of two algorithms: Autoregressive Integrated Moving Average (ARIMA) from traditional statistical models and Gated Recurrent Unit (GRU) from deep learning frameworks. The results indicated that the GRU outperformed ARIMA, showcasing its potential for enhanced predictive capabilities. In a case study from Sri Lanka (Peiris et al., 2021) the authors proposed a LevenbergMarquardt (LM) based Artificial Neural Network (ANN) model for predicting potential wind power generation.

Additionally, another study highlighted the efficacy of Genetic Algorithms as a learning algorithm within ANN frameworks, demonstrating superior performance in wind power predictions. Overall, most studies utilize AI or machine learning methods to forecast wind power. Artificial Neural Networks (ANN) were chosen for developing the AI model due to their relative ease of use compared to alternative methods and their high accuracy.

Moreover, ANN is well-suited for modeling nonlinear relationships and is integrated into several simulation software platforms. The algorithm proposed in study (Fernandes & Yen, 2021) is capable of identifying three distinct solutions regarding training/test error and computational complexity. These solutions are achieved by removing convolution filters from multiple layers within the network architecture, employing a network pruning method. Similarly, study (Im & Dasari, 2022) utilized network pruning to diminish the computational complexity of deep neural networks. Furthermore, study (Freire et al., 2022) implemented a pruning strategy to achieve a reduction in the computational complexity of neural networks. Study (Hossain et al., 2023) describes various techniques for reducing the computational complexity of deep neural networks. One technique is pruning, which involves removing the least significant learning parameters of deep learning models to lower complexity without compromising performance. Another technique is quantization and model compression, which reduces the precision of the weights and activations of the neural network.

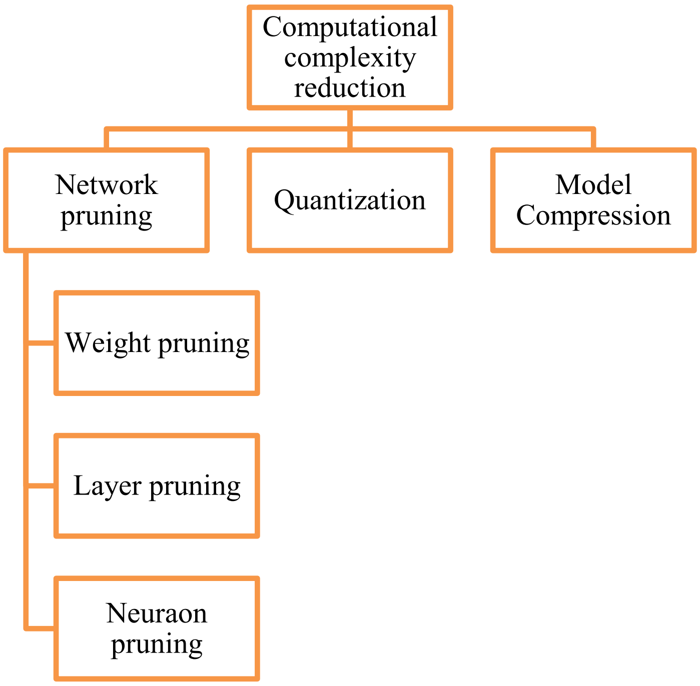

Figure 12. Computational complexity reduction techniques Methodology

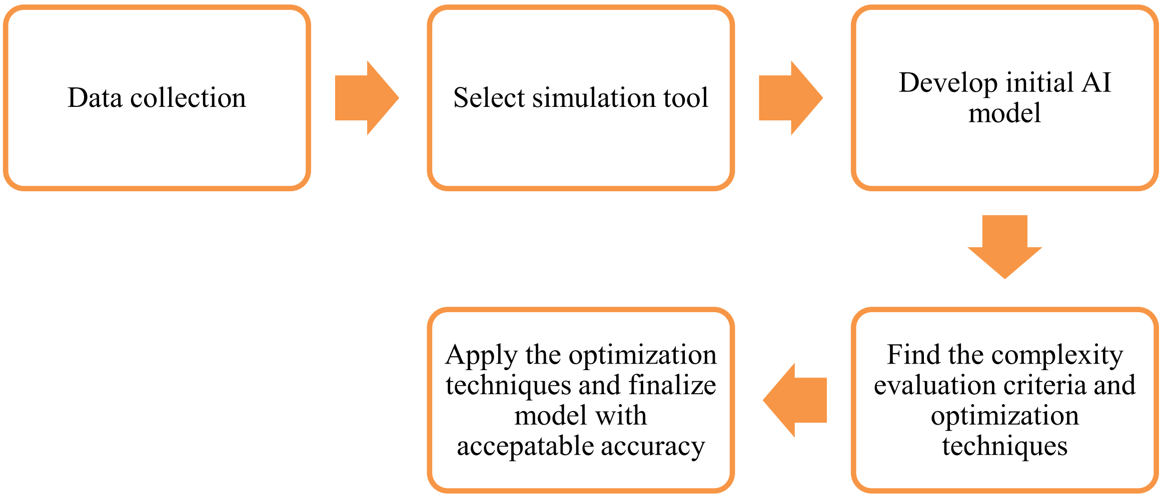

Figure 13. Methodology

DATA COLLECTION

The factors affecting wind energy were classified into two categories: meteorological factors and physical factors. Following the installation of the wind power plant, physical parameters such as rotor diameter and hub height were held constant over time. Therefore, any variations in wind power output were attributed solely to changes in meteorological parameters. As a result, physical parameters were excluded from the model. Only meteorological parameters—such as wind speed, wind direction, relative humidity, rainfall, snowfall, surface pressure, temperature, and air density—were used to train the initial model. All meteorological parameters identified in the literature were utilized in the development of the initial model.

The wind energy generation dataset was referenced in study (Effenberger & Ludwig, 2022) and was downloaded from the website cited in (*Wind Turbine Scada Dataset*, n.d.). This dataset included wind energy, wind speed, and wind direction. The actual location of the wind power plant was identified as HXPR+54J Şenköy, Çınarcık/Yalova, Türkiye. The remaining meteorological data were obtained from a meteorological data collection website (🏛️ *Historical Weather API | Open-Meteo.Com*, n.d.). Subsequently, these datasets were properly combined to create the finalized dataset, which was used to develop the initial model.

Simulation tools

The simulation software gives various machine learning and deep learning techniques to develop AI model. Artificial Neural Networks (ANNs) have proven to be superior to other AI techniques for wind power forecasting due to their ability to effectively model complex non-linear relationships inherent in wind patterns (Peiris et al., 2021). Additionally, ANNs excel in processing large datasets, which is critical for wind forecasting where historical and real-time data from multiple parameters must be analyzed simultaneously. This capability improves the better generalization with large dataset (Hu et al., 2021). Another significant advantage of ANNs is their adaptability to real-time forecasting (Ju et al., 2019). Furthermore, ANNs exhibit robustness when handling noisy or incomplete data, a common challenge in wind power datasets. Techniques such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs) within ANN frameworks have shown greater resilience to data inconsistencies (Qureshi et al., 2023).

INITIAL AI MODEL STRUCTURE

The AI model was trained using the finalized dataset. The software tool was provided with a feature to change the hidden layer size. In the initial model, the hidden layer size was set to 10, which was the default value given by the software. A coefficient of determination of 93.5% was achieved with a hidden layer size of 10. The hidden layer size was then manually adjusted, and the accuracy was evaluated for each configuration. Although the maximum coefficient of determination, 95.1%, was obtained with a hidden layer size of 200.

The coefficient of determination (R^2) (Pham et al., 2019) was used as a key indicator of model accuracy, with a value approaching 1 (or 100%) indicating an excellent fit. The accuracy of the initial model was illustrated in Figure 3.

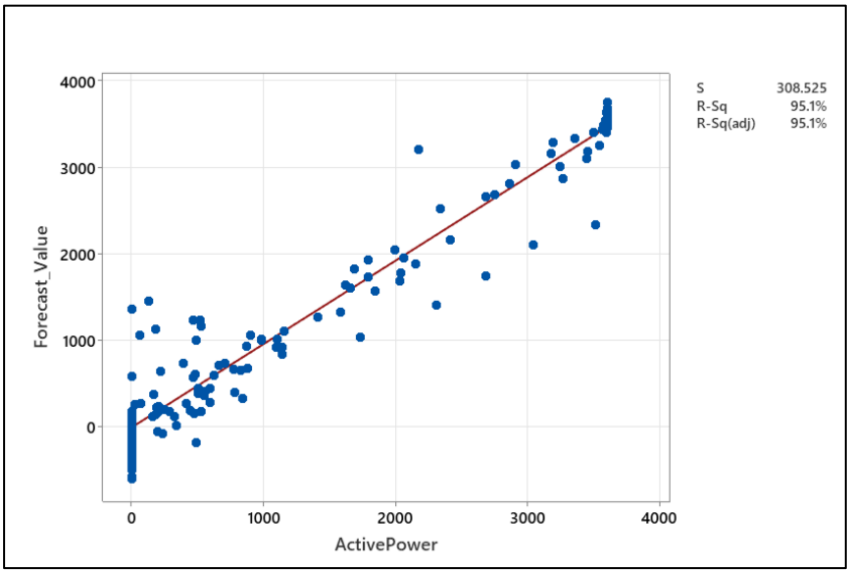

Figure 14. Graph actual power vs model output

Complexity Evaluation Criteria

According to study (Cheng et al., 2020), a higher number of parameters was associated with a more complex model; therefore, the number of parameters was used to determine computational complexity. Study (Han et al., 2016) indicated that larger models consumed more storage and memory, allowing model size to be used as an indicator of efforts to reduce computational complexity. Additionally, if the inference time was high, it resulted in output delays and required greater computational power. Hence, according to study (Wang et al., 2020), inference time was also considered a measure of computational complexity. Study (He, n.d.) reported that models with higher computational complexity typically required longer training times; thus, training time was used as another indicator. Furthermore, according to study (Pham et al., 2019), R^2 and RMSE were applied as accuracy measures of AI models.

Optimization techniques

The computational complexity of an AI model was significantly influenced by its parameters, as these determined the amount of computation required for both training and inference. Therefore, the number of parameters was reduced in order to decrease computational complexity. To support this reduction, the linear relationship between output power and the model's parameters was required to be evaluated, as it could guide effective parameter selection.

In (Ratner, 2009), correlation analysis was employed to assess the linear relationship between two variables. A correlation value close to 1 was interpreted as indicating a perfect positive linear relationship, while a value close to -1 was considered to represent a perfect negative linear relationship. The evaluation criteria, as defined by (Ratner, 2009), were as follows:

Values between 0 and 0.3 (or 0 and −0.3) were interpreted as indicating a weak positive (or negative) linear relationship.

Values between 0.3 and 0.7 (or −0.3 and −0.7) were considered to reflect a moderate positive (or negative) linear relationship.

Values between 0.7 and 1.0 (or −0.7 and −1.0) were taken to indicate a strong positive (or negative) linear relationship.

Table 14. Summary of correlations.

Parameter	Correlation
Wind speed (m/s)	0.935
Wind direction (°)	0.907
Relative humidity (%)	0.305
Rain (mm)	0.1
Surface pressure (Pa)	-0.019
Air density (kg/m^3)	0.115
Snowfall (mm)	-0.038
Temperature (K)	0.274

A significant positive linear relationship was identified between wind speed and wind direction; consequently, these variables were considered essential for the model. Relative humidity and temperature were found to exhibit a moderately positive linear relationship. Rainfall, surface pressure, air density, and snowfall demonstrated weak relationships and were therefore excluded from the original dataset. Subsequently, the model was trained using only wind speed and wind direction, which resulted in low accuracy (51.8%). As a result, relative humidity and temperature were reintroduced into the model. The improvement of the model after removing parameters with weak correlations is demonstrated in Table 3.

Table 15. Improvement of the model

Evaluation Parameters	Initial model	Parameter removed model
Number of parameters	8	4
Model size (KB)	5	5
Inference time (S)	0.019078	0.018402
Training time (S)	10.81253	9.265138
RMSE	308.525	305.882
R^2	95.1%	94.9%

The literature review outlined various methods for reducing computational complexity and provided a brief analysis of these approaches. Network pruning techniques were examined, and weight pruning, layer pruning, and neuron pruning techniques were applied for further modifications. According to (Molchanov et al., n.d.), a pruning ratio of 30% (0.3) was used, meaning that the smallest 30% of the weights (in terms of absolute value) were set to zero.

In weight pruning, if individual weights were less than or equal to 0.3, those weights were removed from the neural network. In layer pruning, if the weights of a layer were less than or equal to 0.3, the entire layer was removed. In neuron pruning, if the weights associated with a neuron were less than or equal to 0.3, the entire neuron was removed from the neural network. The improvement of the model after pruning is demonstrated in Table 4.

Table 16. Improvement of the model after pruning

Evaluation Parameters	**Initial model**	**Parameter removed +pruning**
Number of parameters	8	4
Model size (KB)	5	5
Inference time (S)	0.019078	0.0072
Training time (S)	10.81253	3.11
RMSE	308.525	353.025
R^2	95.1%	93.3%

The literature review outlined various methods for reducing computational complexity and provided a brief analysis of these approaches. Network quantization techniques were examined. Quantization was presented as a model compression technique used in machine learning and deep learning to reduce the memory footprint and computational requirements of neural networks. The improvement of the model after quantization is demonstrated in Table 5.

Table 17. Improvement of the model after quantization

Evaluation Parameters	**Initial model**	**Parameter removed +pruning+ quantization**
Number of parameters	8	4
Model size (KB)	5	4
Inference time (S)	0.019078	0.0069
Training time (S)	10.81253	0.79
RMSE	308.525	379.267
R^2	95.1%	91.3%

RESULTS

The artificial neural network (ANN) model developed for wind power forecasting was shown to have achieved substantial improvements in predictive accuracy as the network architecture was enhanced. The evaluation process was conducted using a systematic approach, in which the model's performance was assessed across various levels of complexity. Table 6 presents the performance comparison between the initial and optimized models.

Table 18. Performance comparison between the initial and optimized models

Evaluation Parameters	**Initial model**	**Parameter removed +pruning+ quantization**	**Percentage improvements**
Number of parameters	8	4	50%
Model size (KB)	5	4	33.3%
Inference time (S)	0.019078	0.0069	63.83%
Training time (S)	10.81253	0.79	92.69%
RMSE	308.525	379.267	-22.94%
R^2	95.1%	91.3%	-3.99%

The initial model was reported to have achieved a final accuracy of 95.1%. A coefficient between 0.7 and 0.9 was interpreted as indicating moderate to strong predictive capability, while an R-squared value exceeding

0.9 was considered indicative of excellent performance. The final model achieved an accuracy of 91.3%, which was regarded as acceptable. Figure 3 illustrates the accuracy of the initial and final models.

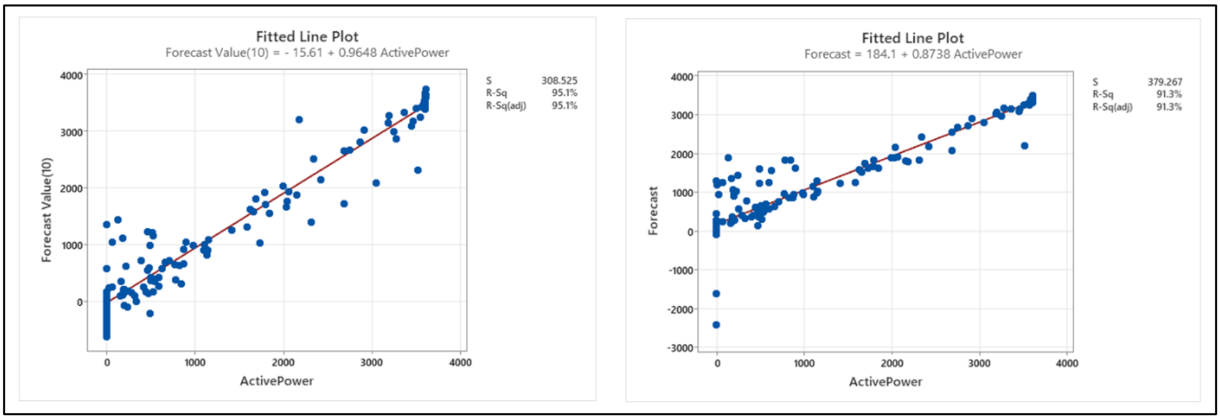

Figure 15. Accuracy of the initial and final models

DISCUSSION

The initial ANN model was successfully developed using eight meteorological parameters and achieved high predictive accuracy, with an R^2 value of 95.1%. Simulation tools were utilized to enable efficient training and validation. Weakly correlated parameters—such as rainfall, surface pressure, and others—were removed to reduce input dimensionality. The application of pruning and quantization techniques further streamlined the model, resulting in a 92.7% reduction in training time and a 63.8% reduction in inference time. Despite these reductions, the optimized model maintained an acceptable level of accuracy, with an R^2 value of 91.3%, demonstrating a practical balance between computational efficiency and predictive capability. The accuracy of an AI model can be reduced by pruning techniques, which work by removing less significant weights, neurons, or entire connections from the network to make it smaller and more efficient.

Training time was reduced from 10.81 seconds to 0.79 seconds, facilitating faster model updates. Additionally, model size was decreased by 33.3%, enhancing its suitability for deployment on edge devices within power grid systems. The reduction in inference time (63.8%) supports real-time implementation in time-sensitive grid management scenarios. While there was a 3.99% decrease in R^2 and a 22.94% increase in RMSE, these changes were considered acceptable given the substantial improvements in speed and resource efficiency. This trade-off aligns with real-world requirements, where lightweight and scalable models are prioritized.

However, it should be noted that the data used—sourced from Türkiye—may not fully capture seasonal variability present in other regions. Moreover, the model's reliance on wind speed wind direction, relative humidity and temperature may limit its accuracy in locations where other meteorological factors, such as turbulence, have a greater impact. For applications in other regions, this model can be further enhanced by incorporating additional parameters to improve its generalization capabilities, suggesting a potential direction for future work.

CONCLUSION

This research developed a short-term ANN-based wind power forecasting model and optimized it through parameter reduction, pruning, and quantization. The final model achieved a 92.7% reduction in training time and a 63.8% improvement in inference speed, while maintaining an accuracy of 91.3% (R^2), demonstrating its suitability for real-time grid applications. The resulting lightweight model enabled faster and decentralized forecasting, thereby enhancing the integration of renewable energy sources. Additionally, the reduced computational requirements allowed deployment on low-power devices, increasing the model’s accessibility and practicality.

Future work will aim to develop a model tailored to diverse wind generation systems. Efforts will also be directed toward reintroducing physical parameters—such as rotor diameter and hub height—to further generalize the model for broader applicability.

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