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# Prediction Error-Based Power Forecasting of Wind Energy System Using Hybrid WT–ROPSO–NARMAX Model

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**Abstract:** The volatility and intermittency of wind energy result in highly unpredictable wind power output, which poses challenges to the stability of the intact power system when integrating large-scale wind power. The accuracy of wind power prediction is critical for maximizing the utilization of wind energy, improving the quality of power supply, and maintaining the stable operation of the power grid. To address this challenge, this paper proposes a novel hybrid forecasting model, referred to as Hybrid WT–PSO–NARMAX, which combines wavelet transform, randomness operator-based particle swarm optimization (ROPSO), and non-linear autoregressive moving average with external inputs (NARMAX). The model is specifically designed for power generation forecasting in wind energy systems, and it incorporates the interactions between the wind system's supervisory control and data acquisition's (SCADA) actual power record and numerical weather prediction (NWP) meteorological data for one year. In the proposed model, wavelet transform is utilized to significantly improve the quality of the chaotic meteorological and SCADA data. The NARMAX techniques are used to map the non-linear relationship between the NWP meteorological variables and SCADA wind power. ROPSO is then employed to optimize the parameters of NARMAX to achieve higher forecasting accuracy. The performance of the proposed model is compared with other forecasting strategies, and it outperforms in terms of forecasting accuracy improvement. Additionally, the proposed Prediction Error-Based Power Forecasting (PEBF) approach is introduced, which retrains the model to update the results whenever the difference between forecasted and actual wind powers exceeds a certain limit. The efficiency of the developed scheme is evaluated through a real case study involving a 180 MW grid-connected wind energy system located in Shenyang, China. The proposed model's forecasting accuracy is evaluated using various assessment metrics, including mean absolute error (MAE) and root mean square error (RMSE), with the average values of MAE and RMSE being 0.27% and 0.30%, respectively. The simulation and numerical results demonstrated that the proposed model accurately predicts wind output power.

**Keywords:** wind power generation; short-term forecasting; artificial neural network (ANN); power forecasting; Shenyang offshore wind power

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## 1. Introduction

Since renewable energy sources like solar and wind are pure and sustainable energy sources, they are becoming more crucial because of the continued depletion of fossil fuels over the past few decades [1]. However, it is well known that the stochastic nature of wind power generation creates significant uncertainties, challenges, and difficulties in electrical power networks. The quality and stability of the power system may be compromised by variations in wind power, and it may also have an impact on market participants who must bear financial losses if the contracted quantity of energy cannot be produced [2]. Hence, numerous tools are required due to a massive want for techniques that can precisely predict wind power production and diminish unwanted impacts of integrating wind energy into an electric power grid. A large number of techniques have been discussed and elaborated on in the literature for wind power forecasting [3]. Many of the methods have been discussed in the literature, and an artificial intelligence-based method is one of them, such as a neural network utilized for forecasting due to high precision in performance. The ANN technique is suitable for the prediction of wind power, and some researchers [4,5] have also proven that it has better forecasting precision.

A recurrent neural network-based method was proposed in [6] for predicting wind power, emphasizing the forecasted system performance; however, the dependency is based on choosing the proper input features, which is a critical choice. Correspondingly, a boundless feature selection is suggested in the study to consider the input feature and use power data and wind speed from the national renewable energy laboratory (NREL). In [7], the time resolution affects the predicted precision with an adaptive time resolution technique that was suggested for the revival of the errors, so that errors in wind power prediction systems using Artificial Neural Networks (ANNs) can be exterminated. The input data was prepared with the perspectives of associating the Harmonic Research Time Series (HANTS), Discrete Wavelet Transform (DWT), and improvised K-means techniques [8].

The primary research content for short-term prediction typically consists of a wind power forecast for the next 72 h. Physical, statistical, and hybrid prediction techniques are the three categories into which prediction technology is divided [9]. Ref. [10] presents a sequence-to-sequence learning-based univariate short-time series technique. While statistical methods excel at short-term prediction, physical methods have exceptional advantages in long-term forecasting [11]. Physical methods must consider the particular geographic surroundings of the wind farm (including data on the terrain, geomorphology, and roughness) [12]. Firstly, numerical simulations are used to forecast future weather conditions using meteorological factors such as air pressure, speed and direction of the wind, temperature obtained through numerical-based weather prediction, and a large amount of meteorological data. The appropriate wind power can be acquired based on the wind power characteristic curve of a wind farm [13,14]. The study in [15] successfully predicted the wind speed 36 *h* ahead by using the regional data based on numerical prediction of the weather and then transforming the predicted results into power values by using the wind turbine's output power characteristic curve. In a study referenced in [16], a wind power forecasting model was developed using physical techniques that indirectly estimated wind power by predicting wind speed under predetermined boundary conditions. The model then obtained a spatial correlation matrix by examining the internal correlation between the output power of the wind turbine and wind speed. Finally, using the wind speed power curve, the wind speed was fitted to the corresponding power. Although this physical method has a longer prediction period and requires a large amount of historical data to conduct multiple calculations, the prediction error is still significant, making it less common in practice.

First, the calculation method is based on a statistical analysis of historical data on wind speed, output power, and wind farms, and the return is determined by the internal road [17], counting Sun and Moon, Markov, Bayes, Pole Learning Machine, Neural Network Autoregressive, and SVM [18,19].

In [20], the authors developed a set of polynomial autoregressive models to forecast wind speed one day in advance, and the findings demonstrated that the PAR model outperformed non-linear models such as artificial neural networks and adaptive neuro-fuzzy reasoning systems. In [21], the authors combined convolutional neural networks and Wavelet Transform to forecast the probability distribution of wind energy and successfully taught the data on wind power's uncertainty through their experiments. Additionally, a novel hybrid logistic regression and deep learning method were proposed in [22] for the classification of hyperspectral data, which demonstrated outstanding performance. Hybrid models are being studied more frequently because single models often lack sufficient generalization capacity or stable performance in predicting wind generation.

Hybrid models combine various prediction models and algorithms, utilizing their strengths while overcoming their weaknesses to produce findings that are more accurate [23]. For instance, to find similar wind speed days with the same trends as the predicted days, a hybrid clustering technique [24] was used. The data from these similar days were then used to train a neural network optimized by Particle Swarm Optimization (PSO) to produce accurate results. Another illustration is a whale algorithm model [25] that was created to improve the Extreme Learning Machine for the aging assessment of Insulated Gate Bipolar Transistor modules to assess the stability of the device's operation. Support Vector Machine (SVM) and Gravitational Search Algorithm (GSA) were combined in [26] to create a classifier that was more accurate, and chaotic search was used to improve the GSA's feature subsets. Additionally, a least-square Support Vector Machine-based hybrid prediction method was put forth in [27]. The optimization of internal parameters was achieved through the Cloud Evolution Algorithm. The wind power data was preprocessed using a two-way comparison for increasing the prediction accuracy. Because of their straightforward structure, strong generalization capabilities, and simplicity in obtaining the global optimum, neural networks are extensively used in prediction models [28]. However, for accurate NN predictions, parameters of non-linear models must be optimized during training, and this can be achieved by utilizing intelligent optimization algorithms.

In [29], a hybrid optimization approach was demonstrated using the backward optimization bat algorithm to optimize the support vector machine (SVM) for predicting wind speed and output power. Simulation results from actual data sets showed that the proposed hybrid model was more effective than using a single SVM. Another study [30] utilized a PSO-optimized SVM model to forecast the total power generation of a microgrid system one day in advance. Although neural network models have been proposed, training their non-linear parameters remains a significant challenge. Meta-heuristic algorithms (MAs) have emerged as powerful optimization tools to overcome this issue. Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Gray Wolf Optimizer, Biogeography-Based Optimization (BBO), Monarch Butterfly Optimization (MBO), and Whale Optimization Problem (WOA) have been used to optimize the nonlinear parameters of neural networks to approximate the nonlinear number. However, when the number of hidden nodes increases, although the advanced MA, multi-learning parameters are also a challenge. Common optimization algorithms, such as PSO, CSO, GWO, and WOA, suffer from local minima and slow convergence issues. Recently, the randomness operator-based particle swarm optimization (ROPSO) algorithm was proposed to overcome these issues. Therefore, this paper proposes a novel ROPSO-optimized nonlinear autoregressive moving average with external inputs (NARMAX) model to solve the wind forecasting problem.

To address the challenges of intermittent and fluctuating wind power in forecasting, researchers have proposed the initial signal sequence by dividing it into several components with distinct prediction guidelines. This approach helps to mitigate interference in different time slots resulting in improvement in the nearly accurate prediction [31]. Various time domain methods, such as empirical mode decomposition, Fourier series analysis, and Wavelet decomposition (WD), have been employed for this purpose [32]. In [33], researchers utilized an artificial bee colony algorithm to optimize the support vector machine (SVM) and applied empirical mode decomposition to minimize errors resulting from significant fluctuations in power output. They developed distinct prediction models for each component and obtained the predicted wind output power. Another study [34] proposed a hybrid model using a combination of empirical mode decomposition and backpropagation to forecast ultra-short-term wind speeds. Additionally, in [35], wavelet denoising was used to decrease the wind speed uncertainty caused by data noise. In theory, the weather is due to the rate of change of wind speed correlates as the fitness function of wind speed. The results show that the number of wind speeds can be refined to damage the difference of random noise and the predictability of sublime numbers.

In this study, a new hybrid model is introduced that utilizes a randomness operator-based particle swarm optimization (ROPSO) algorithm to optimize a neural network-based NARMAX model. Moreover, the Wavelet Decomposition (WD) technique is utilized to preprocess the initial wind power data, address the aforementioned challenges, and attain more precise wind power prediction outcomes. The ROPSO algorithm is advantageous in that it can avoid local optimum locations early on and detect the global optimal solution, which can enhance optimization accuracy and decrease algorithm convergence time. WD decomposes the initial data into more consistent and steady signals, which can enhance the predictability of the data. The experimental results on actual wind farm data demonstrate that the proposed hybrid model possesses better predictive capability in comparison with other existing models. The main contributions of this research include:

1. The fundamental objective of this study is to offer a new and resilient hybrid strategy for wind power forecasting that takes into account the statistical data inputs, such as historical wind power records related to SCADA, and physical data inputs, including historical and future NWP meteorological variables such as wind direction, wind speed, temperature, humidity, and pressure;
2. This paper presents a power level-based prediction scheme designed to address the errors generated by time-based forecasting methods. The approach being described involves using an adaptive neural network for weather forecasting. This allows the network to update its parameters based on current meteorological conditions, which can improve the accuracy of its predictions. The model is trained on historical data but its parameters are continuously adjusted based on new input data. When the error between predicted and actual values exceeds a set limit, the algorithm updates the model's parameters to improve accuracy. This approach is particularly useful for weather forecasting because weather patterns can change rapidly, and current conditions play an important role in predicting future weather;
3. To demonstrate the effectiveness of the proposed prediction scheme, a case study was conducted on a 180 MW wind energy system located in Shenyang city, Shandong Province, China.

The remaining paper is ordered as follows: Section 1. includes the problem statement, data collection WT, NARMAX, ROPSO, implementations of the proposed study and the simulation and numerical results. Section 2 explains the conclusion and future work.

### *1.1. Problem Statement*

For the power prediction of wind energy system time-based predictions schemes, RNN [17,18], CNN [19–21], RBFNN [22–24], and GRNN [21,22] are presented in the previous literature. The issue with the forecast scheme based on timing is that the forecast model is not able to fulfill the forecast error in order to change in climate between the starting time and ending time of the forecast boundary and overcome or manipulate this problem power level-based prediction scheme for wind energy system proposed in this study.

Whenever any discrepancy between predicted and authentic values exceeds a specific limit, the proposed scheme will revise its dynamics based on the prevailing climate change in this power forecasting scheme. This will make the forecasting model more adaptable to the prevailing conditions of the weather. Because the wind power plant is a real-time system, variation in power output can appear immediately in meteorological parameters.

### *1.2. Data Collection and Normalization*

Data collection

The wind power generation data of this survey is from a wind power generation facility in Shenyang City, Shandong Province, China, and it was reported every 5 min, covering 94,270 samples in the 12-month period from 15:05:00 on 9 April 2019 to 23:55:00 on 4 March 2020.

Two datasets were created to develop wind power forecasting models. Dataset 1 contained 86,206 instances and was utilized for model development, while dataset 2, consisting of 8064 instances, served as the four weeks' test data, randomly selected to represent the four seasons in a year: the first week of November (fall), third week of May (spring), third week of August (summer), and fourth week of February (winter).

Data normalization

The data collected in this study contains noise arising from various sources, including maintenance problems, sensor malfunction, and environmental factors such as dirt and ice. To ensure precise forecasting, it is necessary to eliminate the effects of this noise by applying a filtering technique. The collected data is experimental data from the accrual operation data of the Shenyang power plant in China; thus, the chosen data consist of meteorological variables such as wind speed, humidity, temperature, wind direction, and power output value. Five parameters were used as inputs and power was used as an output parameter. The sample training and convergence speed of the model were accelerated and the prediction outcomes were achieved in less time to create the proposed model, which can adapt to the rules of wind power output and can be changed and deduct the impacts of abnormal data on prediction outcomes. The input data are managed to more simple forms before the WT decomposition and NARMAX training.

The data, which includes output of wind power, speed, and direction of wind, are all normalized by the map min: max: function.

$$p_{nor,i} = \frac{p_i - p_{min}}{p_{max} - p_{min}} \tag{1}$$

where $p_{nor,i}$ is the normalized output power value, $p_i$ is the output power value, and $p_{max}$ and $p_{min}$ are the maximum and minimum values of the wind power, respectively.

### *1.3. Proposed Architecture for WT–ROPSO–NARMAX*

#### 1.3.1. Wavelet Transforms (WTs)

The Wavelet Transform (WT) technique is utilized to putrefy the meteorological variable series from Numerical Weather Prediction (NWP) and the Photovoltaic (PV) power series from the SCADA system into respective subseries. This subseries is found to have superior performance characteristics as compared to the original NWP meteorological variables series and SCADA solar power series, enabling more accurate PV power forecasting. The enhanced performance quality of the subseries is attributed to the filtering capability of the WT technique. Continuous wavelets transform (CWT) and Discrete Wavelet Transform (DWT) are the two types of WTs. With regard to a mother wavelet ($x$), the CWT $W(a, b)$ of a signal $f(x)$ is defined as follows:

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(x) \varnothing \left( \frac{x-b}{a} \right) dx \tag{2}$$

where the scaling parameter '$a$' manages the distribution of the wavelet and the translation parameter b is responsible for the central position of the wavelet. The DWT $W(m,n)$ is as accurate as the CWT but more efficient and given by:

$$W(m,n) = 2^{-\frac{m}{2}} \sum_{t=0}^{T-1} f(t) \varphi\left(\frac{t - n2^m}{2^m}\right) \tag{3}$$

where $T$ represents the dimension of the signal, $f(t)$. The scaling and translation parameters are defined in terms of the integer parameters, $m$ and $n$ (i.e., $a = 2^m, b = n2^m$), and $t$ is the discrete time sampling index.

Mallat [36] developed an efficient DWT algorithm that relies on four fundamental filters: the decomposition low-pass, reconstruction low-pass, decomposition high-pass, and reconstruction high-pass filters. This algorithm allows for the quick decomposition and reconstruction of signals. The multiresolution process using Mallat's algorithm involves obtaining "approximations" and "details" from the signal by performing successive decompositions. This results in a hierarchical decomposition procedure with multiple stages, where the original signal is broken down into smaller resolution components.

The mother wavelet $\psi(t)$ used in this study is a Daubechies wavelet of order 4, also known as Db4. This particular wavelet is chosen because it strikes a good balance between smoothness and wavelength, making it well-suited for short-term solar power prediction. Similar wavelets have been employed in prior research for tasks such as load demand forecasting [37,38] and electricity price forecasting [39]. Additionally, this study employs three levels of decomposition, as conducted in Ref. [39], to systematically and reasonably capture the NWP meteorological variables and SCADA PV power series.

### 1.3.2. Randomness Operator-based Particle Swarm Optimization (ROPSO)

The major drawbacks of PSO are trapping into local minima and slow rate of convergence. The trapping into local minima is more dangerous when it comes to the optimization of neural network models. This study presents a randomness operator-based particle swarm optimization (ROPSO) that can handle the slow convergence and local optima of PSO. There is one of the primary concepts too, which relocates the swarm particles in each and every search direction, such as particles that were previously restricted to local optima being dispersed throughout the search gap.

The swarm particle reposition strategy suggested here becomes different from the earlier variants of PSO elaborated in the literature because randomization is applied on each and every search dimension of each particle autonomously.

The proposed swarm particle reposition strategy presented in this paper differs from previous PSO variants described in the literature because it applies randomization independently to each search dimension of each particle. This helps address optimization flaws that are relevant to neural network training. In a comparative performance evaluation presented in [35], ROPSO was compared with PSO and other algorithms. In this study, ROPSO is applied to train a neural network based on the NARMAX model. The ROPSO is initialized with the following basic parameters: a total population of 50, an inertial parameter of $\omega$ = 0.75, acceleration constants of c_1 = c_2 = 2.15, and a maximum of 50 iterations. These parameters are used for NN training with ROPSO. The detailed process of the proposed ROPSO–NARMAX modeling is presented in Figure 1.

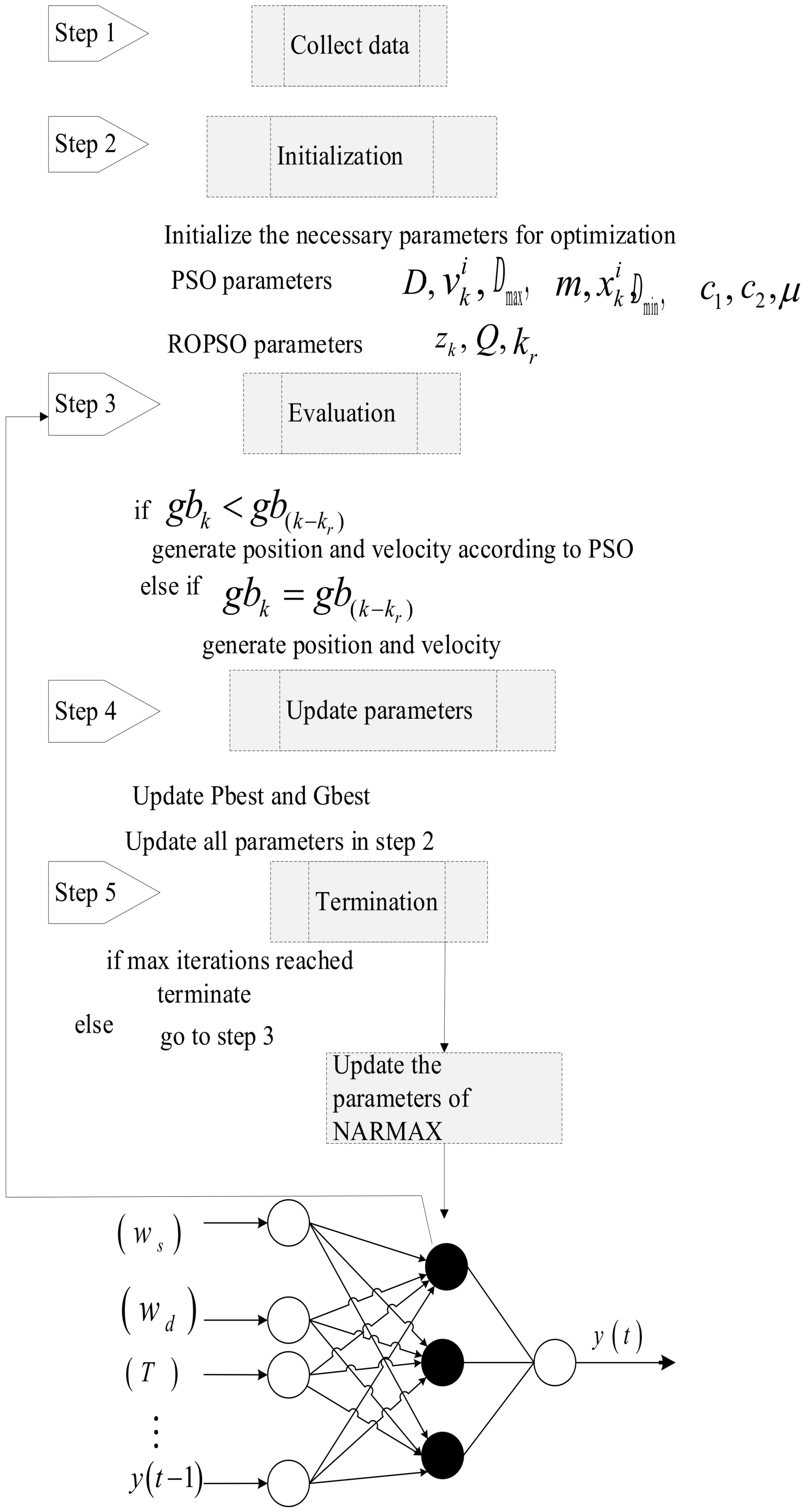


**Figure 1.** ROPSO-based NARMAX model.

#### 1.3.3. NARMAX Model for Nonlinear System

The non-linear autoregressive moving average with external inputs (NARMAX) method delivers a generalized structure for the mathematical modeling of a non-linear system. The NARMAX method utilizes the prevailing and previous input, and the previous output and error commonly express the association between the input and the output of a non-linear, which is dynamic system. The general equation of NARMAX model is given as:

$$y_t = F(y_{t-1}, y_{t-2}, y_{t-3}, \ldots, u_t, u_{t-1}, u_{t-2}, u_{t-3}, \ldots..) + \epsilon_t \quad (4)$$

There are numerous attributes of the behavior of the wind energy system which are elaborated on in the NARMAX model, and this is used for the behavior of the wind energy system which has received the input of prevailing time and the output of the system as well; $y_t$ is the output of the system and $u_t$ is the system input at prevailing time '$t$'. $\epsilon_t$ is the error between the prevailing forecast outputs because the wind energy system is a genuinely non-linear time system; the behavior of the system is well-predicted by the *NARMAX*. The following section shows that the neural network consisting of the identification of the *NARMAX* model for the wind power system is considered in this study.

#### 1.3.4. Neural Network-Based NARMAX Model for Wind Energy System

For the modelling of the wind plant, the NARMAX model is developed on the bases of the wind energy system's measured parameters. The proposed neural network NARMAX model on the bases of the measured parameters of the wind power plant can be defined as:

$$y(t) = F(w_s, w_d, T, y(t-1)) \quad (5)$$

where $F$ is the mapping between wind speed, wind direction, and temperature. The corresponding NN model based upon the above inputs can be described by uniform expression:

$$\begin{gathered} y(t) = \sum_{j-1}^{n} v_j^o \sigma(\sum_{j=1}^{l} v_{ij}\theta_j) \\ \theta_j = 1, 2, 3 \ldots\ldots n \end{gathered} \quad (6)$$

where

$$\begin{gathered} \theta_1(t) = w_s(t) \\ \theta_2(t) = w_d(t) \\ \theta_3(t) = T(t) \\ \theta_4(t) = y(t-1) \end{gathered}$$

where $v_j$ and $v_{ij}$ are the weights of input and hidden layers and $\theta_i$ is the input of neural network, where $i$ = 1,2 … , n. The activation function for the parameters $w_s$, $w_d$, and $T$ are as follows:

$$s_{w_s}(x) = \frac{1}{1+e^{-w_s}} \quad (7)$$

$$s_{w_d}(x) = \frac{1}{1+e^{-w_d}} \quad (8)$$

$$s_T(x) = \frac{1}{1+e^{-T}} \quad (9)$$

The training process of the proposed method is given as

$$J_{min} = \left[y(t) - y^/(t)\right]\left[y(t) - y^/(t)\right]^T \quad (10)$$

where $y(t)$ is the output of the system and $y^/(t)$ is the output of the measured data. $J$ is the Jacobean matrix used to train the LM method. The model will retrain itself whenever the difference between the predicted and measure value is greater than ten percent, i.e.,

$$|y(t-1) - y(t)| > 10\% \quad (11)$$

The neural network based NARMAX model is presented in Figure 2. In this work, the ROPSO optimization approach is used to optimize the parameters of the NARMAX model. The NARMAX parameters are converted to ROPSO parameters and the objective function is given in (10) and is employed as the ROPSO cost function. The goal of the proposed technique is to attain a minimal cost function value. This procedure is repeated until the predicted error achieves the required level. For a particular configuration of the NARMAX structure, the ROPSO optimization method offers the benefit of computational simplicity.

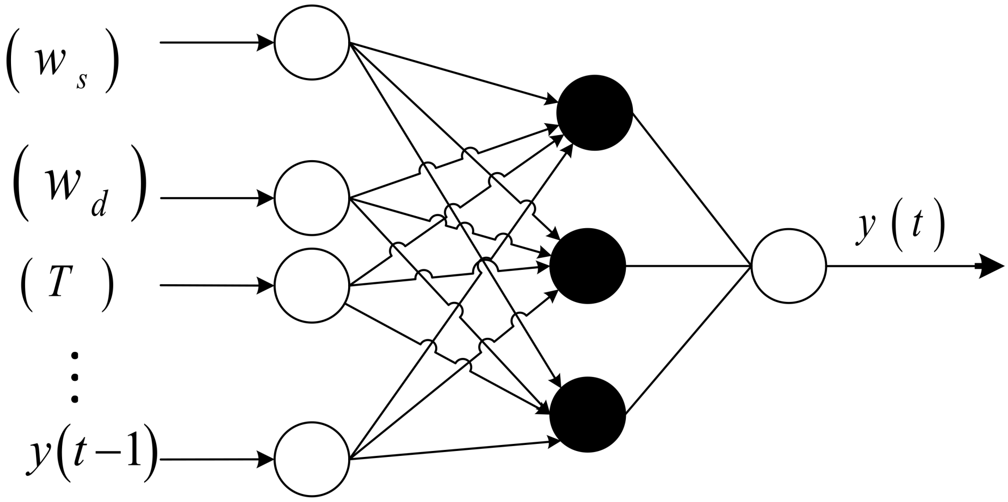


**Figure 2.** NN-based NARMAX Model.

### 1.3.5. Proposed Hybrid Forecasting Model

The explanation of dataset decomposition for NARMAX model is illustrated in Figure 3. The proposed wind energy forecasting technique is implemented using a step-by-step algorithm, as shown in Figure 4. The algorithm uses the wavelet approach for signal decomposition and reconstruction, with the DWT decomposing the preprocessed series into multiple wavelet coefficient signals and one approximation signal.

As illustrated in Figure 4, the preprocessed series is decomposed into six subseries (wind speed, wind direction, temperature, cloud cover, humidity, and pressure) using the DWT. This subseries is then utilized to train the ROPSO–NARMAX model by employing regional NWP meteorological data. This trained NARMAX model can forecast the wind system power output. In the final step, the decomposed future NWP meteorological variables subseries is applied to the trained ROPSO–NARMAX model to forecast the future output power subseries of the wind system. The predicted wind power series of the PV system is then produced by recombining the future power subseries signals.

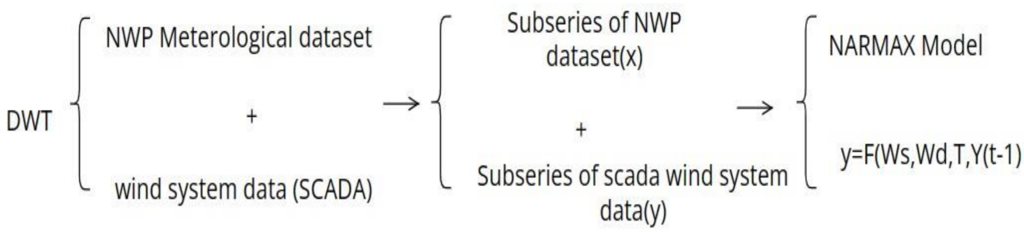


**Figure 3.** Explanation of dataset for NARMAX model for wind prediction.

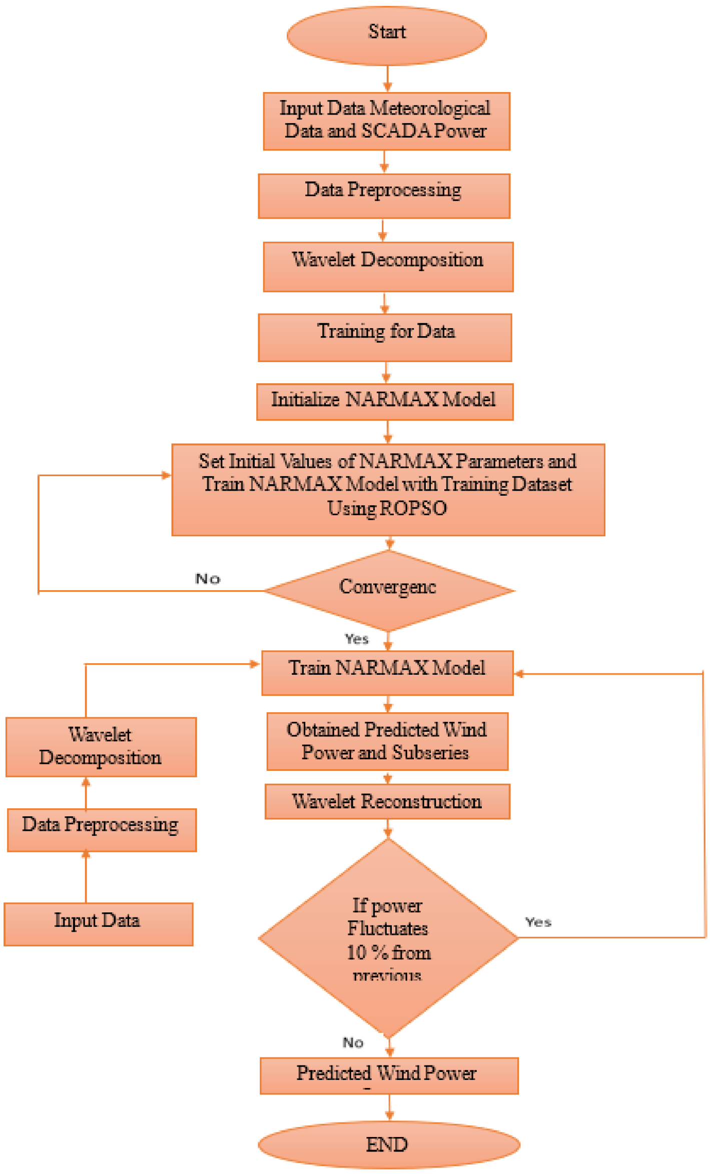


**Figure 4.** Flow chart of the proposed prediction scheme.

### 1.4. Wind Power Forecasting Accuracy Measures

The accuracy of the wind power prediction is evaluated by the mean absolute error (MAE), and the root mean square error (RMSE) is used. The magnitude of error is conceptualized with the help of data units obtained by MAE. The MAE is expressed as follows:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|A_i - f_i| \tag{12}$$

where $N$ is the number of samples, $A_i$ is the actual data, and $f_i$ is the predicted data. RMSE is a commonly used measured of accuracy of time series values. It shows the scattering level produced by the model. The RMSE is expressed as follows:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - f_i)\hat{}2} \tag{13}$$

$N$ is the number of samples, $A_i$ is the actual data, and $f_i$ is the predicted data. Decreased values of MAE, RMSE, and WMAE indicated that the proposed model has good forecasting accuracy.

*1.5. Case Study and Results*

For the evaluation of the suggested prediction project, the forecasting model was applied and used on the Shenyang wind power plant in China, which has a single wind turbine with a capacity of 3000 KW. The power time series and wind speed of *Shenyang* wind farms were taken from 1 January 2020 to 31 December 2020. Figures 5–8 show the comparison of the genuine wind turbine output power with those of the projected output power for wind turbine system for each and every four seasons. The proposed prediction model will retain itself to revive projection standards every time the error between the projected and the genuine power crosses ±10%, carrying out the process of the proposed method.

It is shown in the outcomes, which are elaborated by the suggested scheme adjacent to the line of authentic wind output power, that these all-simulation outcomes have shown that the forecast of the Shenyang wind power plant output nearly corresponds with the authentic recorded wind power, which specifies the effective performance of the elaborated wind power predictor model that has been consummated in the paper.

Moreover, the comparison of the proposed machine learning model is presented in Tables 1 and 2 with respect to different performance metrics. The proposed model is compared with the machine learning methods and other methods that do not use machine learning models.

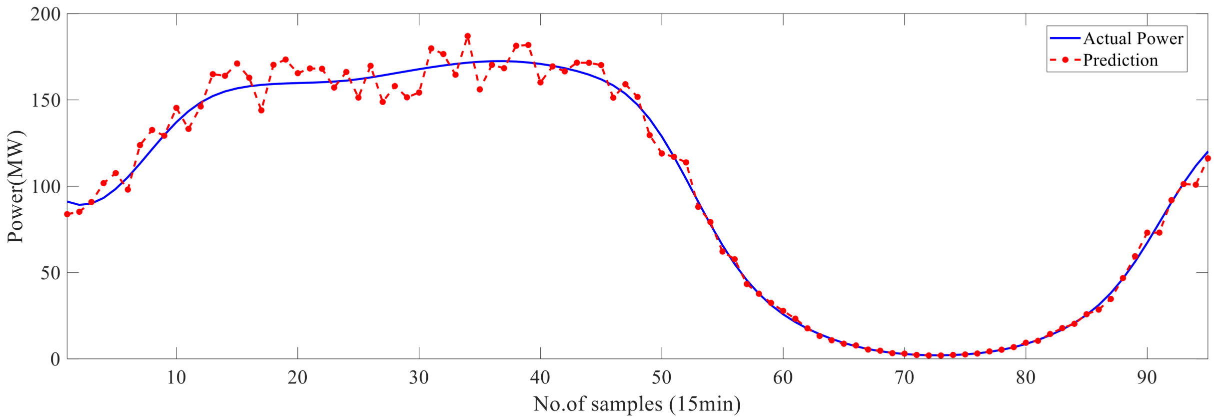


**Figure 5.** Actual and forecasted output power of wind plant for a winter day.

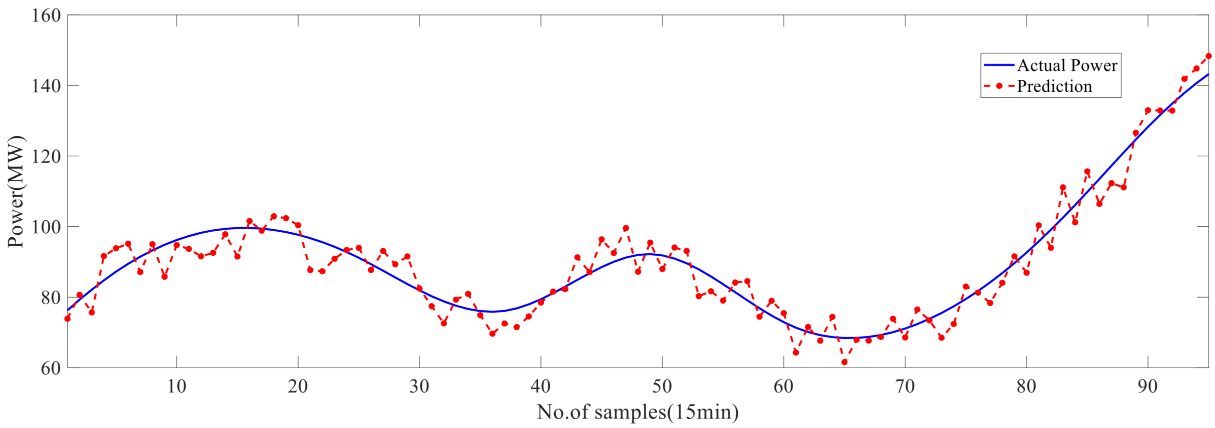


**Figure 6.** Actual and forecasted output power of wind plant for a spring day.

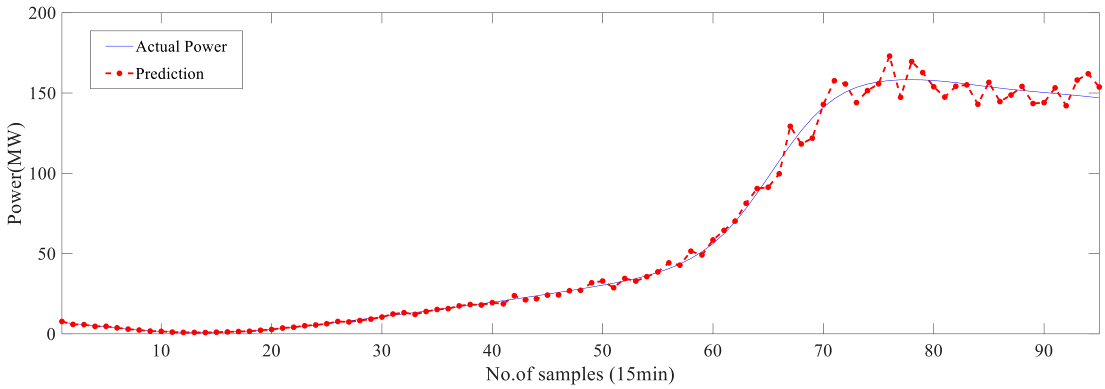


**Figure 7.** Actual and forecasted output power of wind plant for a summer day.

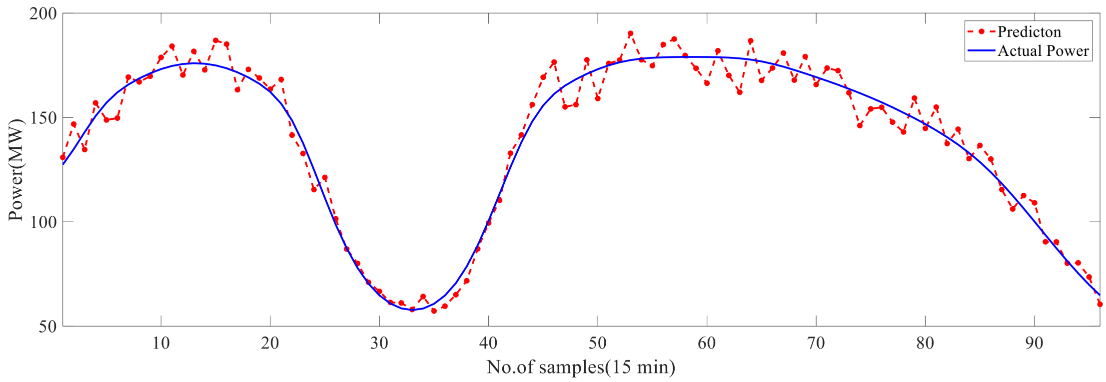


**Figure 8.** Actual and Forecasted output power of wind plant for a fall day.

**Table 1.** Comparison of proposed model for wind prediction with other methods with rest to MAE.

| Forecasting Method | Winter | Spring | Summer | Fall |
|---|---|---|---|---|
| Proposed Model | 0.619 | 0.713 | 0.912 | 0.652 |
| BPNN | 0.8567 | 1.232 | 1.458 | 1.0784 |
| RNN | 0.901 | 1.374 | 1.611 | 1.210 |
| Persistence | 3.162 | 4.023 | 2.581 | 3.798 |
| Markov chain | 4.227 | 4.417 | 5.192 | 4.767 |

**Table 2.** Comparison of proposed model for wind prediction with other methods with rest to RMSE.

| Forecasting Method | Winter | Spring | Summer | Fall |
|---|---|---|---|---|
| Proposed Model | 1.563 | 2.101 | 2.576 | 1.987 |
| RBF-NN | 2.567 | 3.098 | 3.540 | 2.0784 |
| BP-NN | 3.061 | 3.413 | 3.781 | 2.910 |
| Persistence | 5.249 | 5.740 | 6.113 | 5.917 |
| Markov chain | 5.431 | 6.192 | 6.461 | 6.106 |

Table 1 displays the accuracy of the proposed wind power forecasting scheme using the MAE metric. The results indicate that the proposed method exhibits lower error values than other existing prediction methods, as shown in the table.

Similarly, Table 2 provides a comparison of the proposed approach and other methods based on the RMSE metric. Both tables demonstrate that the proposed scheme outperforms other methods in terms of prediction accuracy. The small values of MAE and RMSE obtained in the study confirm the effectiveness of the proposed method for wind power forecasting. Therefore, the results support the significance of the proposed approach for the accurate forecasting of wind power.

## 2. Conclusions and Future Work

In this paper, a new approach for short-term wind power prediction is proposed that combines NARMAX, ROPSO, and WT. The proposed strategy is demonstrated to be effective in predicting wind power output and represents a novel approach to renewable energy forecasting. The use of ROPSO in the training process of NN is shown to be more effective than traditional PSO and GOA due to its ability to solve real-time optimization problems with multiple local optima. A case study on a 100 MW wind energy system in China shows that the proposed hybrid model accurately predicts wind power output, as demonstrated by evaluation metrics MAE and RMSE.

Future work could incorporate model selection methods to further improve the proposed NARMAX–ROPSO–WT model. Additionally, this model has the potential to be used for forecasting power demand, solar generation, and other types of stochastic non-linear forecasting tasks. Overall, this proposed strategy has the potential to make a significant contribution towards shaping a low-carbon energy future.

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## Abbreviations

| | |
|---|---|
| ROPSO | Randomness operator-based particle swarm optimization |
| NARMAX | Non-linear autoregressive moving average with external inputs |
| WT | Wavelet Transform |
| PEBF | Prediction error-based power forecasting |
| ANN | Artificial neural networks |
| MAE | Mean absolute error |
| MSE | Mean square error |
| HANTS | Harmonic Research Time Series |
| DWT | Discrete Wavelet Transform |
| SVM | Support vector machine |
| Mas | Meta-heuristic algorithms |
| GA | Genetic algorithm |
| PSO | Particle swarm optimization |
| GWO | Grey wolf optimizer |
| BBO | Biogeography-based optimization |
| MBO | Monarch butterfly optimization |
| SCADA | Supervisory Control and Data Acquisition |

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