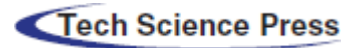


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Design of Neural Network Based Wind Speed Prediction Model Using GWO

R. Kingsy Grace^{1,*} and R. Manimegalai²

¹Department of Computer Science and Engineering, Sri Ramakrishna Engineering College, Coimbatore, 641022, India

²Department of Computer Science and Engineering, PSG Institute of Technology and Applied Research, Coimbatore, 641062, India

*Corresponding Author: R. Kingsy Grace. Email: kingsygrace.r@srec.ac.in

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Abstract: The prediction of wind speed is imperative nowadays due to the increased and effective generation of wind power. Wind power is the clean, free and conservative renewable energy. It is necessary to predict the wind speed, to implement wind power generation. This paper proposes a new model, named WT-GWO-BPNN, by integrating Wavelet Transform (WT), Back Propagation Neural Network (BPNN) and Grey Wolf Optimization (GWO). The wavelet transform is adopted to decompose the original time series data (wind speed) into approximation and detailed band. GWO – BPNN is applied to predict the wind speed. GWO is used to optimize the parameters of back propagation neural network and to improve the convergence state. This work uses wind power data of six months with 25, 086 data points to test and verify the performance of the proposed model. The proposed work, WT-GWO-BPNN, predicts the wind speed using a three-step procedure and provides better results. Mean Absolute Error (MAE), Mean Squared Error (MSE), Mean absolute percentage error (MAPE) and Root mean squared error (RMSE) are calculated to validate the performance of the proposed model. Experimental results demonstrate that the proposed model has better performance when compared to other methods in the literature.

Keywords: Wind speed; wavelet transform; back propagation neural network; grey wolf optimization; time series

1 Introduction

The rapid growth of the world economy, the renewable energy sources such as solar, tidal, wind and geothermal energy has significantly shown its importance around the globe. Wind power is one of the most powerful ways to generate electricity from renewable sources. The amount of wind around the wind farm must be estimated to forecast the wind power. Wind speed is an important factor that affects the wind power. The other factors include location of wind farm and weather. There are two types of wind speed predictions, namely, short term and long term based on the time scale of the prediction. The former is more reliable than the later [1]. Numerical-Weather-Predictions [2] are based on physical methods and the statistical methods. They are also based on the historical data and not on the meteorological data such as temperature, pressure, surface conditions and obstacles. Time series data are used for the estimation of wind speed in statistical methods along with artificial intelligence.

Statistical and physical methods are also named as direct and indirect methods respectively. In direct method, there is a linear relationship among input time series data and the predicted results. Some of the direct method for prediction of wind speed are presented in [3–9]. Examples of indirect method for wind speed forecasting are reported in [10–12]. Both physical and statistical methods are also combined to provide better prediction of wind speed [13]. The reliability of the wind speed prediction is improved in hybrid approaches in Osório et al. [14–17]. Most of the proposed techniques use single learners and

those are not steady in most of the changing weather conditions. If more predictors are included simultaneously, it increases the prediction error.

In Zhou et al. [17], after splitting into low frequency and high frequency data, two networks are used to train the input time series data. This will increase the prediction model's memory usage and computation cost. The proposed model WT-GWO-BPNN has single network with two hidden layers. To avoid the local minima and the over fitting problem, a Meta-heuristic algorithm, GWO is used. The steps involved in the proposed work are as follows: (i) A reliable wind speed prediction strategy is proposed and the wind speed is predicted with the help of wavelet transform, GWO and back propagation neural network. (ii) WT-GWO-BPNN is suitable for any type of wind farms and can be adopted for both wind power prediction and wind speed prediction. This paper is organized as follows. The related work in the literature is discussed in Section 2. Section 3 explains the preliminaries such as WT, BPNN and GWO. The proposed model WT-GWO-BPNN is presented in section 4 and the results are summarized in section 5. Section 6 concludes the paper with future directions.

2 Preliminaries

2.1 Wavelet Transform

WT is one of the prevailing tools to analyze variety of resolution images and time series data. During wavelet analysis the input signal is decomposed into shifted wavelets and scaled wavelets. Sparse representation and non-redundant computation are the advantages of DWT than the Fourier Transform (FT), and Gabor transform while extracting features. DWT has been successfully used for feature extraction and achieve better results when compared to other methods [18]. DWT is a suitable method for extracting features of time series data. Furthermore, it allows the analysis of time series data on well localized in both time and frequency domain. Input data decomposition is done using Low Pass Filter (LPF) and High Pass Filter (HPF). At first level decomposition input image is divided into two components: approximation and detailed sub-band. The output of LPF is approximation band and the output of HPF is detailed sub-band. The vertical band, horizontal band and diagonal band are the three sub-bands in the detailed input signal. In approximation band further decomposition is done to divide into approximation and detailed data, and so on. The levels of decomposition can be determined based on the application [18].

2.2 BPNN

BPNN is a variety of ANN, supervised learning, multilayer feed-forward network. The layers in BPNN are input layer, multiple hidden layers and output layer [19]. Fig. 1 shows the general structure of BPNN. The input data is processed by the input layer. All the neurons in the input layer are communicated with the hidden layer through a communication link named weight. The weight is multiplied with the input and the result is added with bias. Output neuron is computed based on the activation function.

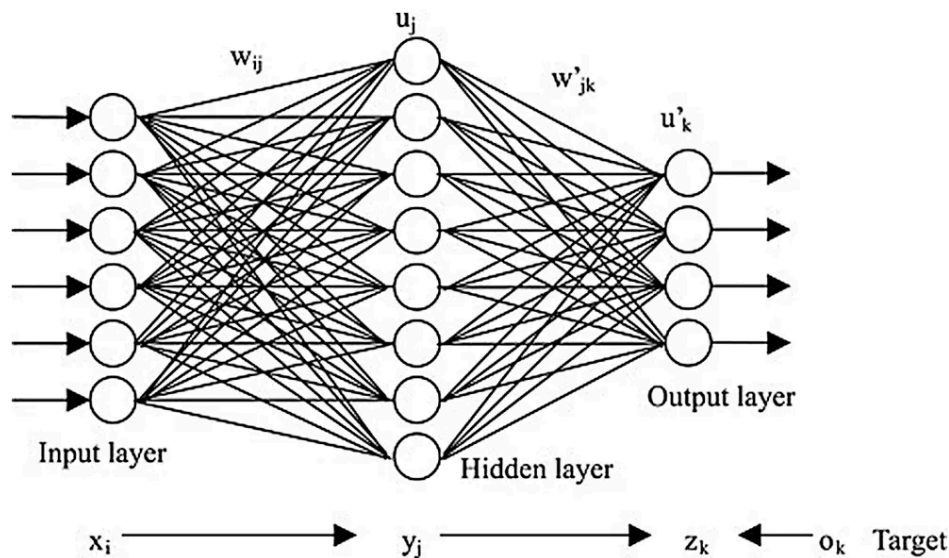


Figure 1: General structure of BPNN

$$I_K = \sum_{i=1}^n X_i W_i \quad (1)$$

$$Y_K = \emptyset (I_K + B_K) \quad (2)$$

Eq. (2) defines the output of the neuron K. X_i indicates the input, W_i indicates the weights, input adder is represented by I, B is bias, output is Y and the activation function is \emptyset . In this method, BPNN is designed with an input layer, two hidden layers and an output layer. The number of neurons in the input layer depends on the number of feature vectors. The number of hidden layers and their neurons. Each hidden layer consists of 25 neurons. The number of output neurons in the output layer is equal to the number of registered individuals. Hidden layers activation function is Tan sigmoidal function. Purelin is employed as a transfer function in the output layer.

2.3 Grey Wolf Optimizer (GWO)

The GWO is one of the meta-heuristic algorithms based on the grey wolf's hunting style [3]. The four varieties of grey wolves are: (i) alpha (ii) beta (iii) delta and (iv) omega. These variations are based on their leadership ladder. The hunting tread of grey wolves are: (i) searching for victim (ii) encircling victim and (iii) attacking the victim. Among the three classifications of the meta-heuristics, GWO comes under Swarm Intelligence (SI) algorithms and the others are evolutionary algorithms and physics-based algorithms. Some of the SI algorithms [20] are: MBO [21], AFSA [22], Termite Algorithm [23], Wasp Swarm Algorithm [24], Monkey Search [25], BCPA [26], Cuckoo Search [27], DPO [28], Firefly Algorithm [29], BMO [30], Krill Herd [31], FOA [32]. The Canidae family of grey wolf is in the crest of the food chain. Wolf are lived in a group average of 5 to 12. Fig. 2 shows the social ladder of grey wolf. The alphas are leaders and either male or female are in charge for all activities. The decision made by the alphas is followed by the betas. Scapegoat role is played by the omega which is in the lowest ladder. Delta is lower to alpha and beta and upper to omega. Deltas are usually the boundary keepers.

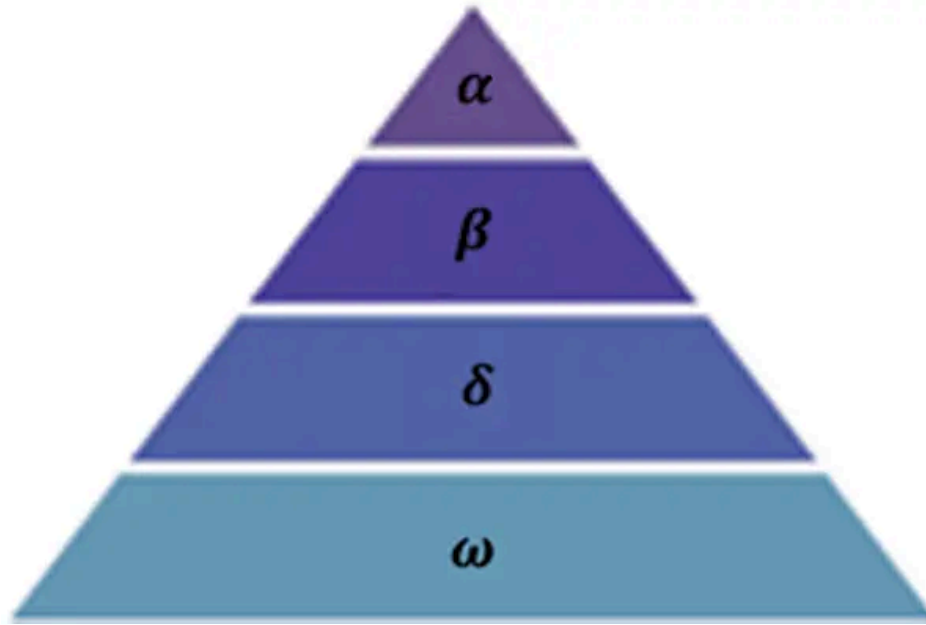


Figure 2: Grey wolf ladder [20]

In GWO α is the fittest solution and β , δ and Ω are the subsequent solutions. The mathematical equations in the GWO are given Eqs. (3) to (9) [20].

$$D = C \cdot X_p(t) - X(t) \quad (3)$$

$$X(t+1) = X_p(t) - A \cdot D \quad (4)$$

$$A = 2a \cdot r_1 - a \quad (5)$$

$$C = 2 \cdot r_2 \quad (6)$$

$$D_\alpha = |C \cdot X_\alpha - X|, D_\beta = |C_2 \cdot X_\beta - X|, D_\delta = |C_3 \cdot X_\delta - X| \quad (7)$$

$$X = X_\alpha - A_1 \cdot (D_\alpha), X_2 = X_\beta - A_2 \cdot (D_\beta), X_3 = X_\delta - A_3 \cdot (D_\delta) \quad (8)$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \quad (9)$$

Where A and C are the coefficient vectors. The position of victim is X_p and the position of grey wolf is X. Both X_p and X are vectors. Vector a is decline from 2 to 0. The random vectors r1 and r2 takes the

values in the range of $[0,1]$. The GWO algorithm is used to select the best solution from all the iterations. Coefficients A and C are random values and have different hyper-sphere for each random value. The GWO algorithm provides the possible solution to find the position of the victim and is shown in Fig. 3.

Step 1: The population of the grey wolf is initialized as $X_i = 1,2,3,\dots,n$
 Step 2: The random vectors a, A and C are initialized.
 Step 3: Calculate the fitness of search agents $X_\alpha, X_\beta, X_\delta$.
 Step 4: Maximum number of iteration is set as t.
 Step 5: Equation (9) is used to calculate the position of the search agents.
 Step 6: Subsequently calculate the values of vectors a, A and C.
 Step 7: Find the fitness of all the search agents.
 Step 8: Find the best agent based on the fitness value.
 Step 9: Increment the iteration and the iteration is not equal to t goto step 5.
 Step 10: Else return the search agents X_α

Figure 3: GWO algorithm

3 Related Work

This section presents details of some of the prediction models of wind speed available in the literature. Jianguo Zhou et al. have proposed a wind power forecasting named ESMD-PSO-ELM [17]. It is a combination of three algorithms. The ESMD algorithm is used to split the wind energy into two components such as one residual and many intrinsic mode functions [17]. Both the components act as inputs to the hybrid PSO-ELM. The model developed in Zhou et al. [17] used the one-month data of April 2016 which has 2880 observations. The dataset was from china. The proposed model ESMD-PSO-ELM was compared with eight existing models in terms of MAPE (4.76), MAE (2.23) and RMSE (2.70). Aqsa and Asifullah have presented a wind power prediction model using ATL-DNN [33]. This method is a hybrid of transfer learning and deep learning. Intra TL and inter TL are the two classification of base learners training. The proposed algorithm is implemented using Matlab 2015(b) with DBN-Toolbox. The proposed method provides better results, when compared to ARIMA and SVR [33].

Han et al. [34] have introduced a wind power prediction based on Principle Component Analysis and Phase Space Reconstruction (PSR). The former used phase dimension and the latter used phase space reconstruction. The variance of forecasting is very small when compared to other approaches. The machine learning methods such as BPN, RBF and NARX are used for wind speed forecasting in [35] by Senthil Kumar. Significant features are selected from data set to minimize the complications in the prediction model. The proposed models demonstrated good results in terms of RMSE and MAE. Mutual information (MI) based feature selection is carried out. Six models are tested and the NARX with MIFS performs better than other algorithms. Wenlong Fu et al. [36] have introduced using GWO-SCA algorithm. The developed algorithm predicts the wind speed for short-term and multi-step. The designed method is named as IHGWOSCA and estimated optimal values are in PSR and ELM. The OVMD model performs better in terms of RMSE, MAE and MAPE than the standard models and PSR and ELM is better for multi-step prediction. IHGWOSCA converges faster than the other models [36].

Fredy H. Martínez S et al. [37] have discussed the prediction of wind speed with the help of LSTM. The wind energy is based on the speed of the wind in the corresponding area which is having wind farm. The proposed model is implemented using TensorFlow and backend with Keras. 10 years data is collected from Guajira and is the lowest electrical supply area. By predicting the wind speed, the power station in Jepirachi wind farm [38] can estimate the power generation through the farm. The LSTM method is not compared with any other methods but the RMSE value of LSTM is calculated as 4.223 km/h. Hao-FanYang et al. [39] have used E-S-ELM model to predict the wind speed. The proposed model is the combination of auto-encoders and ELM. This deep learning-based method uses 50 hidden layers and suggested to use shared hidden layers to improve the performance.

Jinli Dou et al. [40] have introduced CNN based wind speed prediction model for short-term. CNN plays a major role for improving time correlation between data among different stations. The prediction error rate is less in CNN. Hourly prediction on wind speed is proposed in [41] by Ghorban et al. using machine learning algorithm. Multi-Layer Perceptron (MLP) with feed forward technique, Genetic Programming (GP), multiple linear regression and Persistence method are used in the proposed system. seven years data is used for training and one year data is used for testing. 14 models are tested for both ANN and GP. Hui Liu et al. [42] have developed a wind prediction algorithm based on SSA, CNN, GRU and SVR was named SSA-CNNGRU-SVR. The input wind speed data is split into trend component

using CNNGRU and detailed component using SVR. Even though SSA is extracting features efficiently, the proposed model predicts wind speed with satisfactory level.

Younes et al. [43] have explored both temporal and spatial forecasting of wind speed using ANN. The BPNN, RBFNN and ANFIS prediction models are evaluated. The BPNN learning algorithm [43] uses termination criteria to reduce the error rate during training. RBFNN is similar to BPNN and the algorithm of RBFNN is in Haque [44]. The properties of ANN and fuzzy is combined in ANFIS. The short-term wind prediction model is performed in two groups with the knowledge from the preceding step. The BPNN model prediction is efficient than other models RBFNN and ANFIS. Deep learning-based prediction of wind is explored in [45]. Tao et al. have tested the proposed neural network model deep belief network (DBN) to reduce the ambiguity and volatility nature of the wind power production. The prediction errors are very less in the proposed DBN method.

In order to predict wind power, a hybrid deep learning neural network system has proposed in Liu et al. [46]. The hybrid model consists of WT, Elman network and LSTM. After WT, the low frequency is given as input to LSTM and high frequency is given as input to elman network. Results are tabulated for 3-step predictions. Low and high frequencies are given to two separate networks and requires more memory during training. In Basaran Filik et al. [47], a multi-variable model using ANN is suggested. Three types of ANN network are tested for three substations in Eskisehir. The proposed network in Fonte Deea et al. [48] uses three-layer feed forward pattern and the MSE is less in training, testing and validation set. The DNN-MRT algorithm is proposed by Qureshi et al. in [49] for wind energy prediction wherein base-regressors and meta-regressors are used. The former is deep auto-encoders for training and the latter is DBN for learning. The transfer learning concept is used for reducing the shortcomings and the better learning is ensured by the proposed method ensemble based DNN-MRT. Tab. 1 presents the comparison on various wind speed prediction methods in the literature.

Table 1: Comparison of wind speed prediction models

| S. No. | Methodology | Dataset Count/Year/ Location | Performance Parameters | Used Models | Results |
|--------|------------------------------------|---|---|--|---|
| 1. | ESMD-PSO-ELM [17] | 2880/April 2016/China | MAPE, MAE, RMSE | BPNN, ELM, PSO-ELN, EMD- BPNN, EMD- ELM, EMD -PSO-ELM, ESMD- BPNN, ESMD- ELM, | MAPE is 4.76, MAE is 2.23 and RMSE is 2.70 |
| 2. | ATL-DNN [33] | 13-17 months of 5 wind form data | Mean-Absolute-Error, Root-Mean-Squared-Error, and Standard-Deviation-Error | ARIMA, SVR (linear kernel), SVR (rbf kernel) | MAE is 0.0637, MSE is 0.0986, SDE is 0.0984 |
| 3. | Machine Learning [35] | 2013 to 2015/ University of Waterloo weather station | RMSE and MAE | BPN, RBF, NARX, BPN with MIFS, RBF with MIFS, NARX with MIFS | RMSE is 0.5814 MAE is 0.4381 |
| 4. | IHGWOSCA [36] | 7200/2017/Sotavento Galicia (SG) wind farm and Inner Mongolia (IM) wind farm | RMSE, MAE and MAPE | GS-SVM, GS-BP, GS-ELM, Original-IHGWOSCA-PSR-ELM, Original-SSA-IHGWOSCA-PSR-ELM, OVMD-SSA-CC-PSR-ELM, EMD-IHGWOSCA-PSR-ELM, OVMD-IHGWOSCA-PSR-ELM, EMD-SSA-IHGWOSCA-PSR-ELM, OVMD-SSA-IHGWOSCA-PSR-ELM | RMSE is 0.0675 MAE is 0.0531 MAPE is 0.9169 |
| 5. | Long Short-Term Memory (LSTM) [38] | 10 Years/ Guajira (Colombia) | Root Mean Squared Error (RMSE) | - | RMSE is 4.223 km/h |
| 6. | E-S-ELM [39] | January 2013 to 31st December 2014/five airports in U.K. | Average accuracy, MAPE, VAPE, R ² | EMD-SAE, EMD-ELM, and SAE-ELM | Average accuracy is 93.73 |
| 7. | CNN [40] | - | Root mean square error, Average absolute error | FNN, CNN (1 layer), CNN (2 layers), CNN (2 hours) | CNN (2 layers) E _{min} is 13.63% E _{min} is 9.15% |
| 8. | Machine Learning Techniques [41] | 8 years (2005-2011)/ Kersey site, Colorado, USA | correlation coefficient, root mean square error, Nash-Sutcliffe efficiency coefficient and Akaike information criterion | MLP, ANN, Genetic Programming, Persistence method | ANN CC is 0.892 RMSE is 0.839 E is 0.796 AIC is -1803.2 |
| 9. | SSA-CNNGRU-SVR [42] | 2688 each /April 2015 to May 2015, May 2016 to June 2016, September 2014 /China | MAPE, MAE, RMSE | ARIMA model, PM model, GRU model, LSTM model, CNNGRU model, hybrid SSA-SVR model and hybrid SSA-CNNGRU model | MAPE is 0.97 MAE is 0.11 RMSE is 0.15 |
| 10. | BPNN [43] | Iran | MAPE, MAE, RMSE, WSHE, MAWEEE | RBFNN, ANFIS | WSHE is 2.6% |
| 11. | Deep Belief Network (DBN) [45] | three months data/China | MSE, MAE | NNSHL, NNMHL, SVR | DBN has less error in prediction |
| 12. | EWT-LSTM-Elman [46] | 700 samples | MAPE, MAE, RMSE | ARIMA, GRNN, Elman, EWT-Elman, BP, LSTM, EWT-BP, WPD-LSTM-Elman, EWD-LSTM-Elman | EWT-LSTM-Elman model depicts best performance |
| 13. | ANN [47] | 2 March and 2 April 2016 / Eskisehir | RMSE, MAE | - | RMSE is 0.6508 MAE is 0.5046 |
| 14. | ANN [48] | 2003 and 2004 / Faro, Portugal | MSE | - | MSE is 1.288 |
| 15. | DNN-MRT [49] | five wind farms / Europe | RMSE, MAE, SDE | ARIMA, SVR | DNN-MRT performs better |

4 WT-GWO-BPNN

The proposed model WT-GWO-BPNN is used to predict the wind speed. The WT algorithm is used for decomposing the input signal ie., time series data. GWO-BPNN is used for predicting the wind speed based on the characteristics of the time series data. In this model GWO is used for tuning the weights during the BPNN training. The wind speed data is taken from the publicly available data sources for six months. Tab. 2 describes the statistical values of the input wind speed data. The flow of WT-GWO-BPNN is shown in Fig. 4.

Table 2: The statistical values of wind speed data

| Sample | Mean | Median | Minimum | Maximum | Std. | Skewness | Kurtosis |
|--------|-------|--------|---------|---------|------|----------|----------|
| 25086 | 13.48 | 12.9 | 0 | 58.4 | 6.54 | 0.724 | 3.914 |

Usually, MAPE – Mean Absolute Percentage Error, MAE – Mean Absolute Error, RMSE – Root Mean Square Error and MSE – Mean Square Error are the performance measures for any predictive model [17]. At each input data point, the relative mean value is called as MAPE. The average distance between the actual value and the predicted value is called as MAE. The average magnitude of error is MSE and quadratic scoring of MSE is RMSE. The lower the error values show that there is less variation between the predicted and actual values [50]. Tab. 3 describes the evaluation parameters such as MSE, MAE, RMSE and MAPE used in the proposed model.

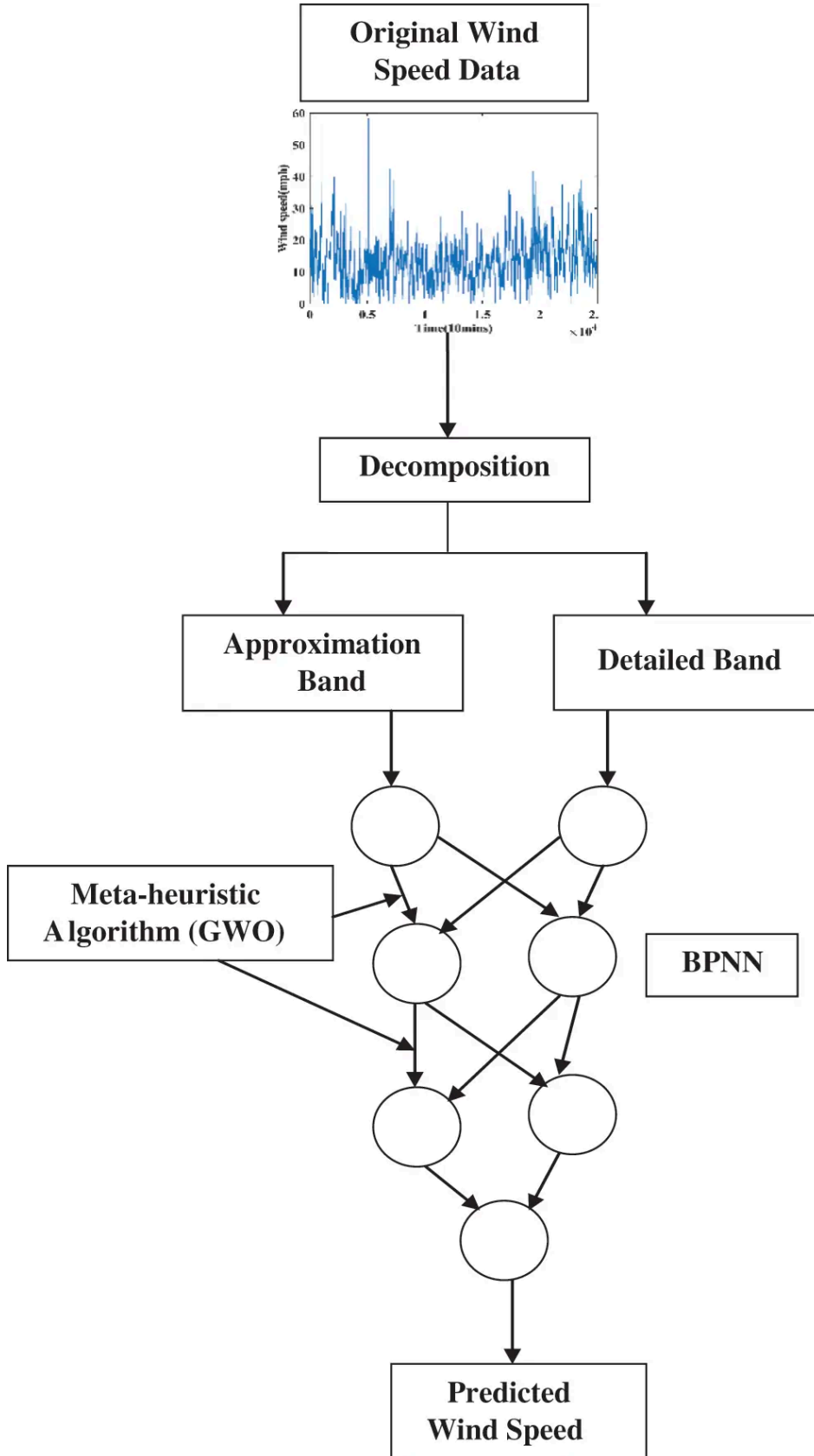
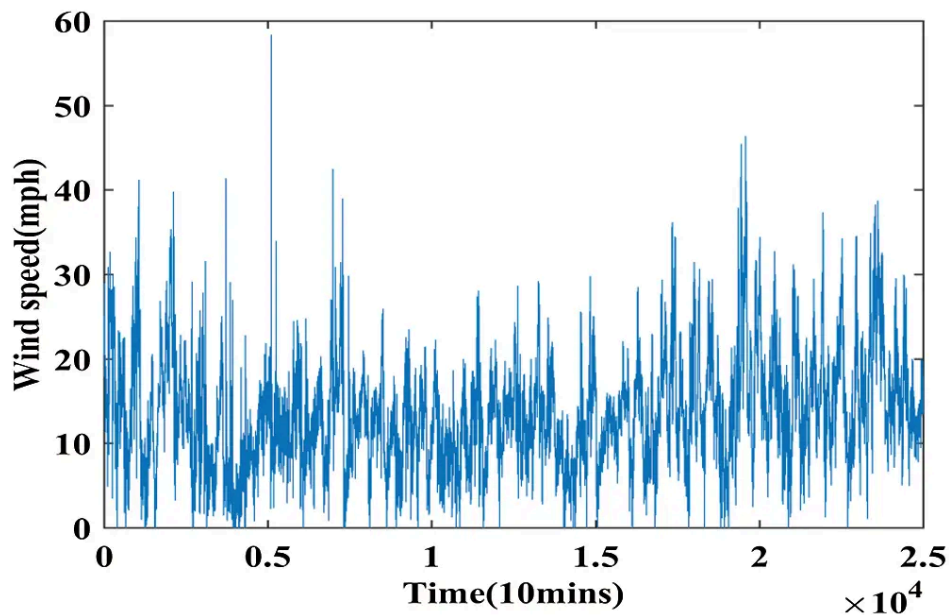


Figure 4: The flow chart of the proposed WT-GWO-BPNN model**Table 3:** Evaluation parameters

| Evaluation parameters | Formula |
|-----------------------------------|--|
| MSE | $MSE = \frac{1}{N} \sum_{k=1}^N (A_k - P_k)^2$ |
| MAE | $MAE = \frac{1}{N} \sum_{k=1}^N A_k - P_k $ |
| RMSE | $RMSE = \sqrt{\frac{1}{N} \sum_{k=1}^N (A_k - P_k)^2}$ |
| MAPE | $MAPE = \frac{1}{N} \sum_{k=1}^N \left \frac{A_k - P_k}{A_k} \right $ |
| A-Actual value, P-Predicted value | |

5 Results and Discussion

This section deals with the experimental results obtained using the proposed system WT-GWO-BPNN. 25,086 data points are chosen as input for prediction. Seventy percentage of input data points are considered for training and remaining thirty percentage for testing. Fig. 5 indicates the original time series data of wind speed collected from internet sources. Initially, WT is applied on the dataset to split the input data into approximation band and detailed band. Fig. 6 shows the approximation band up to three levels. Fig. 7 indicates the detailed band for three levels. The prediction of training data and the testing data is illustrated in Figs. 8 and 9. From Figs. 8 and 9, it is obtained that the proposed method WT-GWO-BPNN performs better during prediction of wind speed.

**Figure 5:** Time series of wind speed

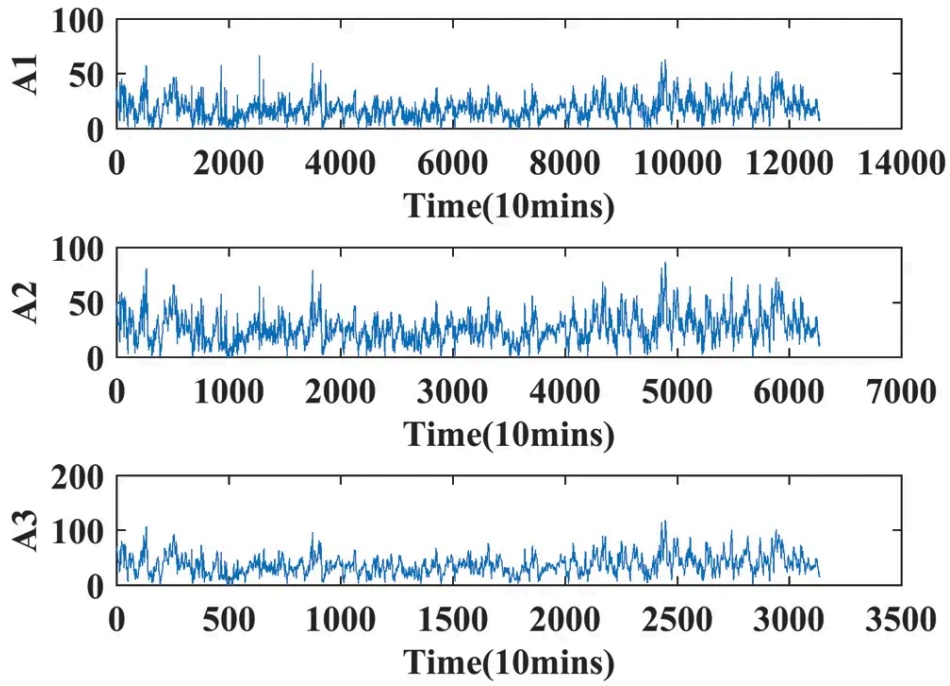


Figure 6: The approximation band of winder speed using WT

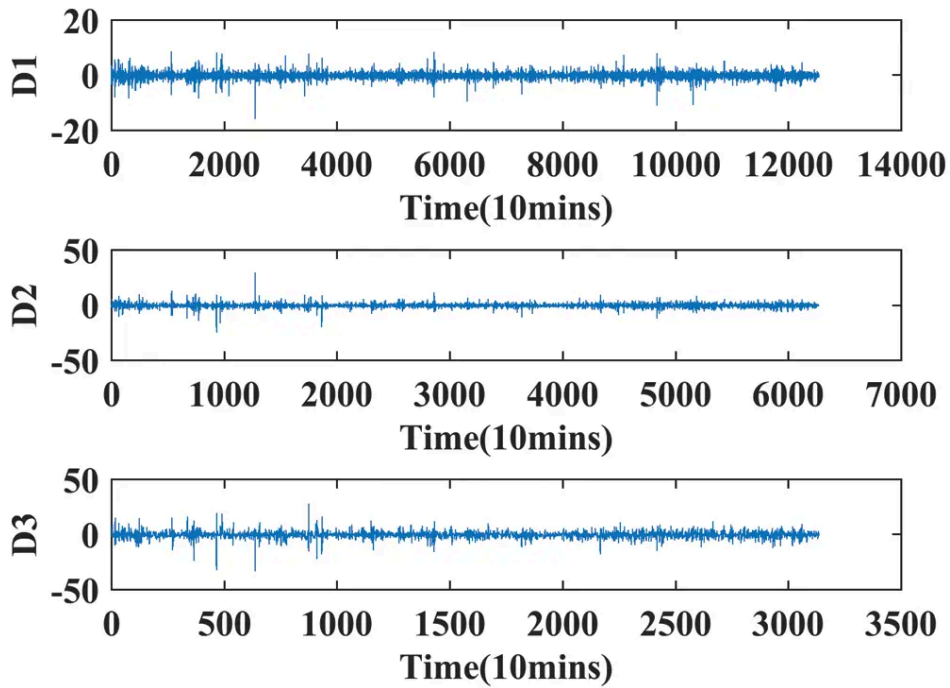


Figure 7: The detailed band of winder speed using WT

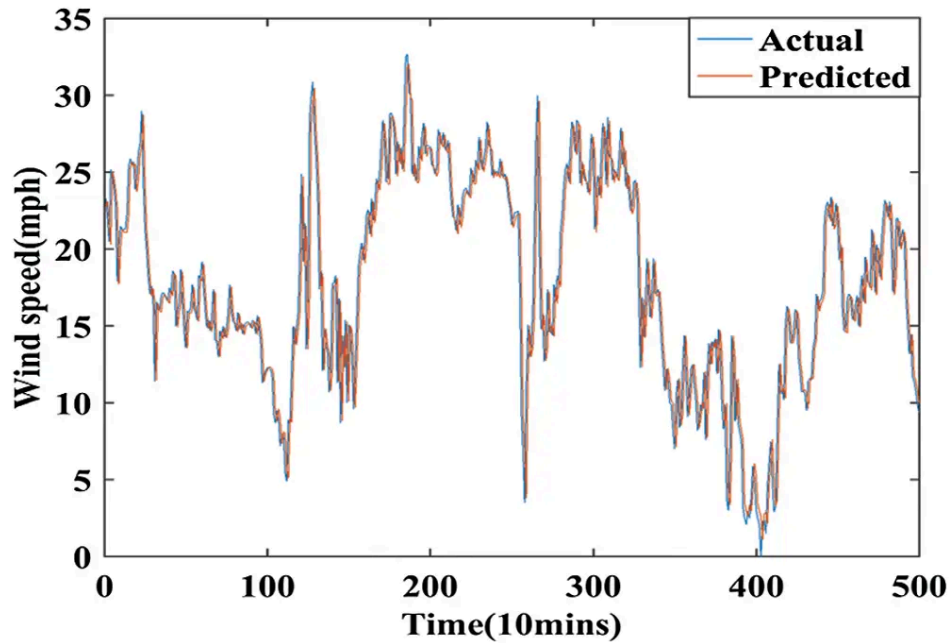


Figure 8: The prediction results of training data

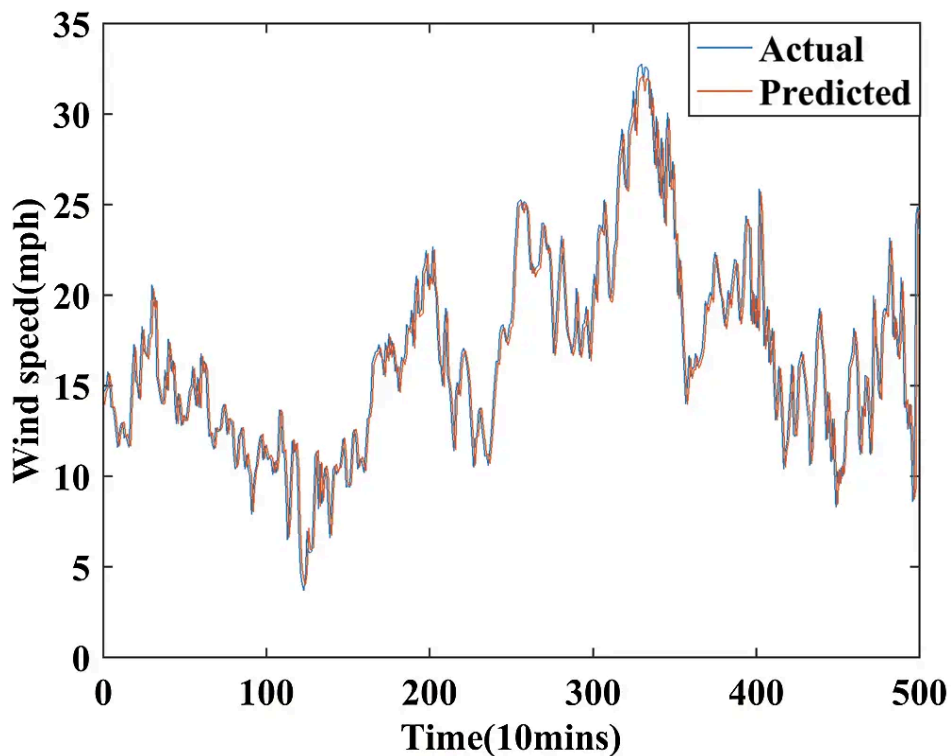


Figure 9: The prediction results of testing data

The error for training and testing data is shown in Figs. 10 and Fig. 11 respectively. As in Figs. 10 and 11, it is observed that the testing error is very less when compared to the training error. Tab. 4 summarizes 1-step, 2-step and 3-step performance comparison on different performance parameters for the proposed system WT-GWO-BPNN. The proposed system is compared with Elman [46], ARIMA [46], WPD-ELM [17], GRNN [46], EWT-Elman [46] and BPNN [17] in the literature and provides better results in terms of the performance parameters such as MSE, MAE, RMSE and MAPE. From Fig. 12, it is quite clear that the proposed model provides better results than other models taken for comparison.

Table 4: Stepwise performance comparison of WT-GWO-BPNN

| Performance Metrics | 1-Step | 2-Step | 3-Step |
|---------------------|--------|--------|--------|
| MSE | 2.69 | 4.95 | 6.62 |
| RMSE | 1.64 | 2.22 | 2.57 |
| MAE | 1.13 | 1.54 | 1.80 |
| MAPE (%) | 11.68 | 16.28 | 19.03 |

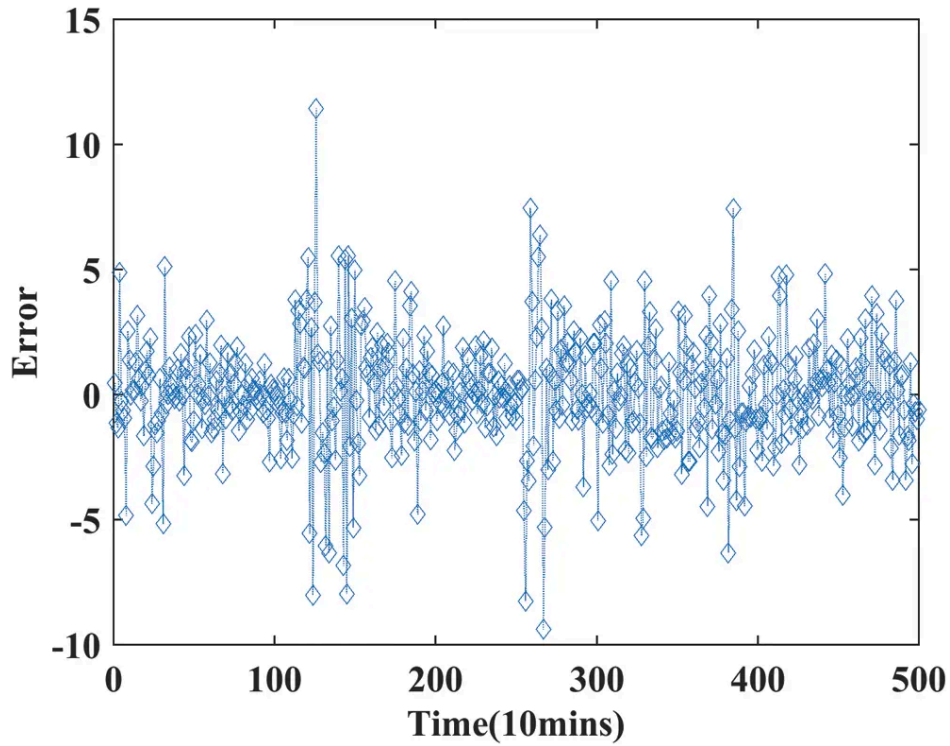


Figure 10: Error for training data

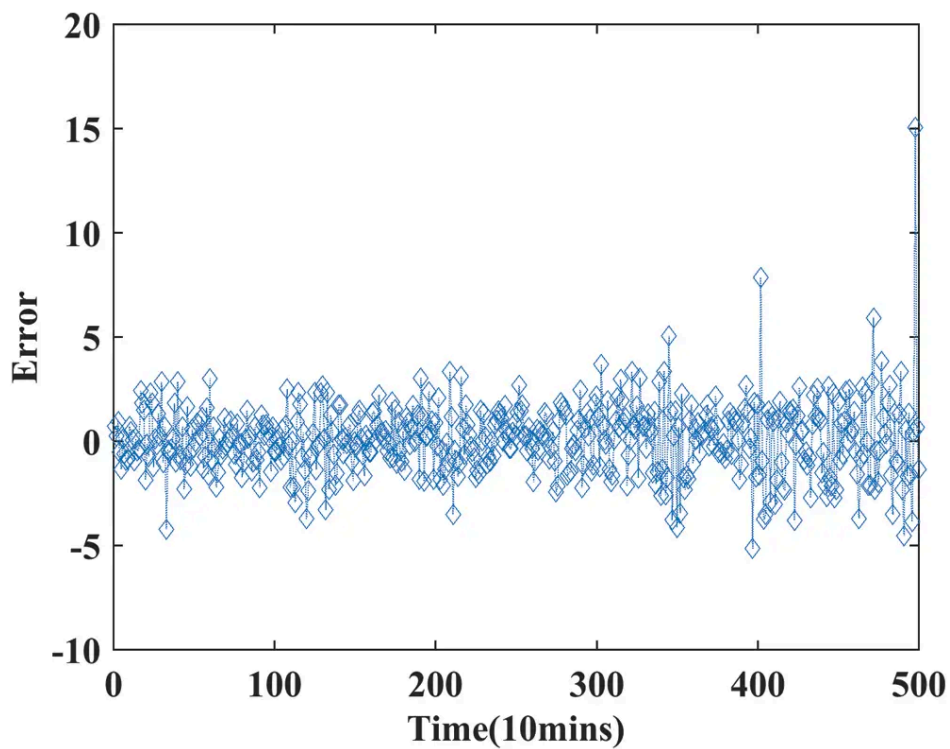


Figure 11: Error for testing data

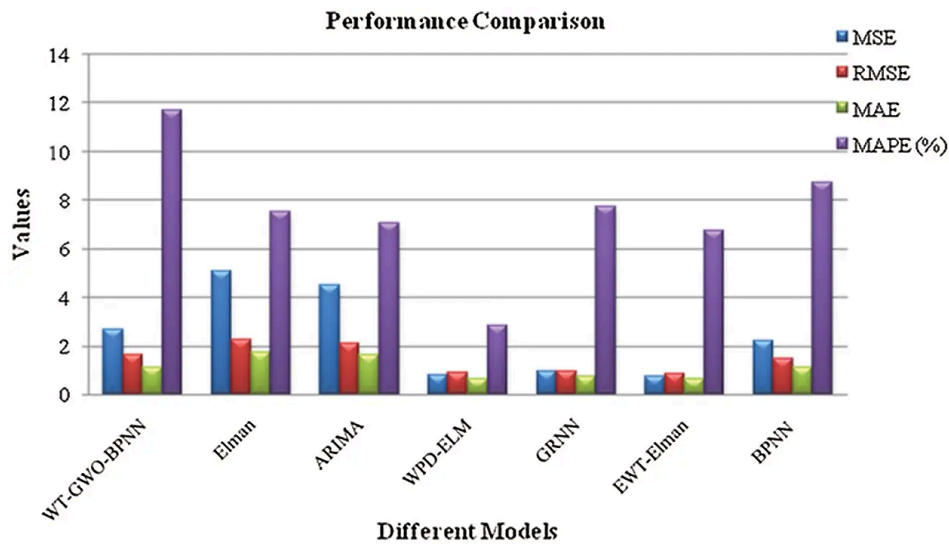


Figure 12: Performance metrics comparison of WT-GWO-BPNN with other models

6 Conclusions

Wind speed is one of the sources of renewable energy. Wind speed prediction is required to predict wind power. Due to the vague environment, the wind speed prediction is more difficult process. This paper has presented a wind speed prediction model employing a hybrid method named as WT-GWO-BPNN. The proposed method uses six months wind speed data of about 25,086 samples for prediction. The performance of the proposed model is evaluated and compared with the existing models in terms of MSE, MAE, RMSE and MAPE. It is observed that the proposed model poses low MAE when compared to all other models such as Elman, ARIMA, WPD-ELM, GRNN, EWT-Elman and BPNN. Additionally, the value of MSE and RMSE is better than Elman, ARIMA and BPNN. Stepwise performance comparison of WT-GWO-BPNN proved that the proposed method is used for prediction of wind speed during climatic changes. In future research, deep neural network methodologies can be applied with more sample data to improve the prediction of wind speed.

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