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A Comparative Study of Adaptive Neuro Fuzzy Inference System and Support Vector Regression for Forecasting Wind Power

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Abstract: The forecast of the power generated by a wind power plant is a process that wind farm companies need to do every day. Electrical system manager uses these forecasts to plan the next day's electrical generation. Thus, while generation-consumption balance in the grid is maintained, numbers of reserve power plants are decreased. Wind power has uncertainty as it depends on nature. Therefore, wind speed forecasts and wind direction forecasts of the power plant area are generally used in wind power forecasts. In this study, hourly wind power generation of next day is forecasted by using Adaptive Neuro Fuzzy Inference System (ANFIS) and Support Vector Regression (SVR) methods. The hour of day, wind speed forecast and wind direction forecast are the inputs of the forecast system. One-year data are selected as training data, six-mount data are forecasted. Five different models are formed by using the system inputs in different configurations and final forecast are found by averaging the model forecasts. The average normalized mean absolute error values are found 10.86 and 10.8 with ANFIS and SVR, respectively.

Keywords: *Adaptive Neuro Fuzzy Inference System, ANFIS, Energy management, Support Vector Regression, Wind power forecasting.*

1. Introduction

Demand for electricity increases with the increase in population and new power plants need to be installed to meet this demand. Looking at the sources of electricity generation, each country primarily uses its own resources in electricity generation to provide economic benefits. According to the sources of electricity generation in the last 15 years, it is seen that there is an increase in natural gas and renewable energy while decreasing energy obtained from coal and nuclear [1]. The use of fossil fuels in the generation of electricity has caused environmental problems such as global warming and air pollution, and this forced the countries to follow policies to move towards renewable energy. Therefore, the unions and states declared some targets to increase the share of their renewable energy generation in total electricity. While the Europa Union is planning to get of 20% of their electricity from renewable energy sources by the 2020, the United States aims to achieve 30% renewable electricity use by 2025 [2], [3].

Wind power is one of the most rapidly growing renewable energy sources because of its high cost-stability. Especially in last decade, it is very attractive option for utilities, independent power companies and producers. According to the Global Wind Report 2017 published by Global Wind Energy Council, the installed wind power capacity in 2017 grew by 10.6 percent and reached about 5347 GW [4], [5].

While the quantity to be generated can be easily adjusted in conventional energy generation, generation in wind energy cannot be adjusted in this way. Wind power is considered as nondispactable because of its randomness and intermittence. This uncertainty brings about a great impact on power system operation in various aspects, e.g. power system stability and power quality [6]. Wind power forecasts helps in eliminating these uncertainties. This increases both the security of the system and increases the efficiency of the power system by helping to reduce the number of reserve power plants. Wind power forecasts can be classified as long, medium, short and very short according to the forecast time intervals. While long-term forecasts are used for wind power planning and power system planning, medium-term forecasts are preferred to solve unit commitment and maintenance scheduling problems. Short-term forecasts help in reserve control and economic distribution problems, while very short-term forecasts are mainly used in areas such as wind turbine control and power system frequency [6].

Especially in systems with large-scale wind power integration, wind power forecasting affects the whole the electrical system reliability, electricity generation scheduling and electricity prices. In addition, wind power forecasting is also very important for Wind Power Plant (WPP) owners. It effects the bid price of spot market and penalties resulting from forecast errors, thus it plays a crucial role in company profitability. In the Dutch system for example, 120 Euro penalty is applied for each MWh energy that was projected to be supplied but actually not supplied. Penalties for forecast errors and wrong stock market bids caused by forecast errors cost almost 10 percent of all wind power income for wind power companies [7]. In literature, there are some short-term wind power forecasting studies using regression [8], artificial neural network (ANN) [9], adaptive neuro fuzzy inference system (ANFIS) [1], [10], support vector regression (SVR) [11, 12], times series [13], wavelet [14], ensemble methods [15].

In this study using the wind speed forecast and wind direction forecast values of seven WPPs, one day ahead hourly short-term wind power forecast is carried. One-year data are selected as train data, six-mount of data are forecasted. Five different models are formed by using the system inputs in different configurations and the proposed forecast is done by using the ANFIS and SVR methods. Final forecasts are found by averaging the forecast of the

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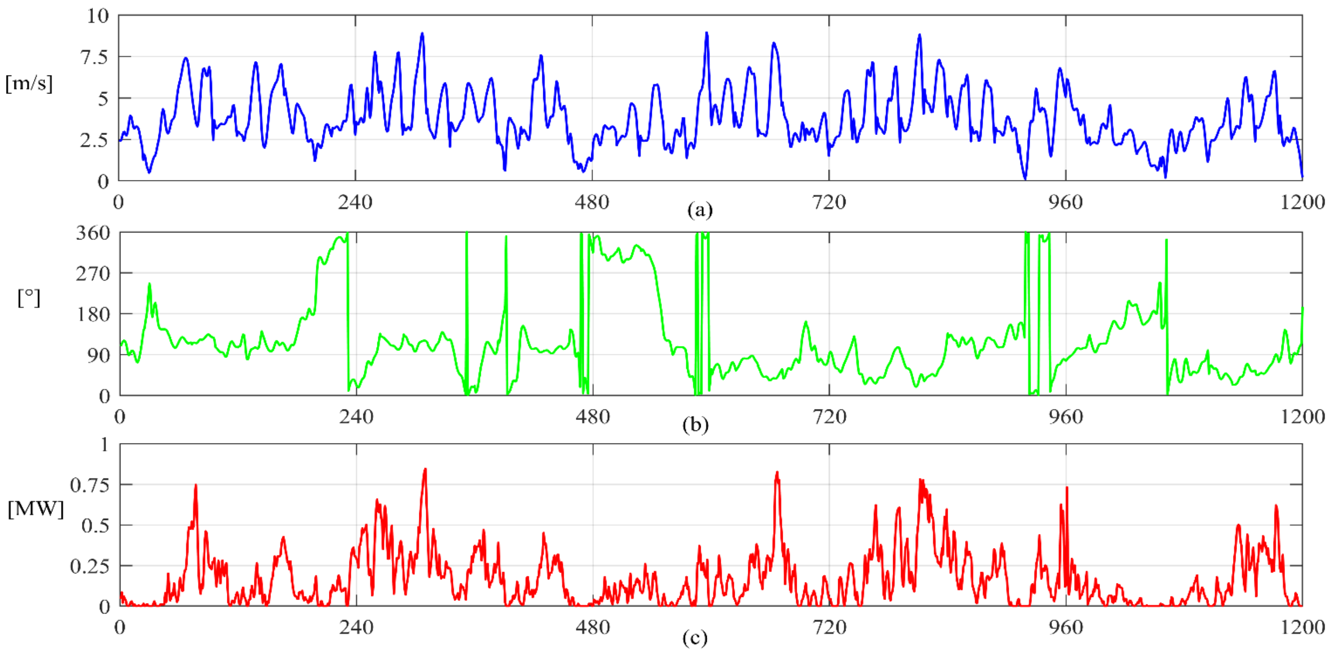

Fig. 1. (a) Wind speed forecasts of WPP 1 (b) Wind direction forecasts of WPP 1 (c) Generated wind power of WPP1

models. This study is an extended version of the previous study [10]. In the previous study, ANFIS models are used as forecast method and results of ANFIS models are averaged. In this study, in addition to ANFIS method, SVR method is also used and these two methods are compared with each other.

The rest of paper is organized as follows. Section 2 gives information about data and formed forecast models. While Section 3 presents the used methods which are ANFIS and SVR, the results are given in Section 4. Section 5 concludes the study.

2. Models

Having the actual power generation data of wind turbine plants is difficult for the researchers working on this subject, because these data are considered a trade secret by WPP companies. In addition to that some turbine manufactures have made agreements with WPP owners to not share these data. The data used in this study is taken from the Global Energy Forecasting Competition and contain measurements of the seven different wind power plants and meteorological forecasts (MF) of the regions where these plants are located. Hourly based measurement data are normalized between 0-1 to mask the characteristic of the wind power plant. MF includes wind speeds and directions at a height of 10 meter for next 48 hours and this forecast is updated in every 12 hours. One year of data are used for training whereas six mount of data is forecasts [16]. In Fig. 1, wind speed forecast, wind direction and generated power of WPP 1 can be seen in hourly bases for four-months period.

Five different models are formed to get the lower forecast error values. In the first three models, different MF which are made at different times are used. As mentioned before MF had made in every 12 hours for next 48 hours. These models are illustrated in Fig. 2 and the coloured green, yellow and blue are correspond the Model 1, 2, 3 respectively. The red part shows the forecasted wind power. t=0 indicates the moment when the forecast will be made. Model 1 uses MF values that made 24 hours before the moment forecast is made. The MF values in the time span 0-24, placed where Model 1 is written, are used as shown in the figure. Model 2 uses MF values that made 12 hours before the moment forecast is made. The MF values in the time span 0-24, placed where Model 1 is written, are used. And lastly Model 3 uses MF values that made the moment the forecast is made. The MF values in the time span 0-24, placed where Model 3 is written, are used.

In Model 4 and Model 5, MF which are used in Model 3 are preferred. Differently, MF are divided into classes according to the determined data intervals. Different forecast structures are applied for each classes. Forecasted wind speed data are in the range of 0-12m/s. These are divided into classes as 0-2 m/s, 2-4 m/s, 4-6 m/s, 6-8 m/s and 8-12 m/s for Model 4. In Model 5, forecasted wind directions are divided six parts as 0-60, 60-120, 120-180, 180-240, 240-300 and 300-360 degree. The forms of the models are illustrated in Fig. 3

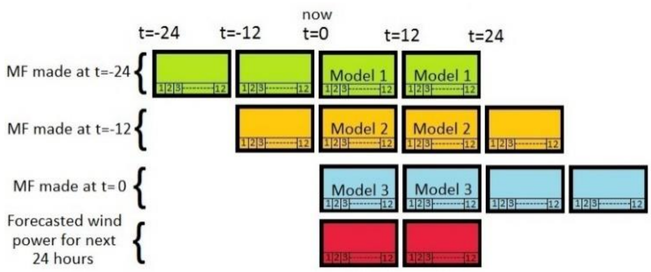

Fig. 2. The forms of Model 1, 2, 3

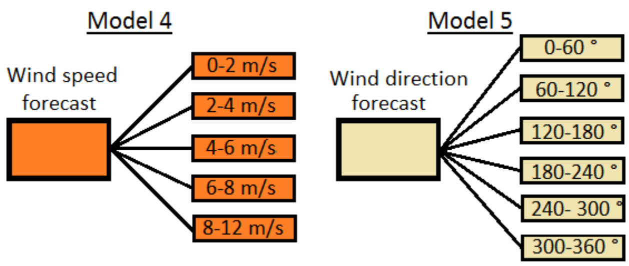

Fig. 3. The forms of Model 4 and Model 5

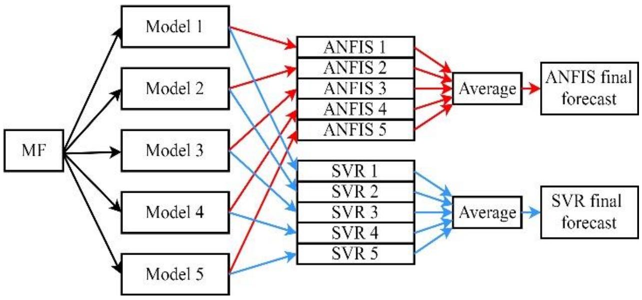

Fig. 4. The flowchart of the proposed system

The proposed forecasting system are illustrated in Fig. 4. It consists of three stage and uses ANFIS and SVR methods. In first stage, five different models are formed as mentioned above by using the system inputs in different configurations. Secondly five different ANFIS structures and five different SVR structures are created for each models. In the last stage, the outputs of ANFIS and SVR structures are averaged separately. Finally, the averaged results are the final forecast values.

3. Methods

3.1. Artificial Neural Fuzzy Inference System (ANFIS)

ANFIS is a hybrid method which is composed of fuzzy logic and artificial neural network. At the beginning of the 1990s, ANFIS is developed by Jang. The fuzzy inference has the advantages of being easy to implement, expressing with linguistic variables, modelling uncertain and non-linear situations. But it has no learning ability instead of this an expert opinion is needed to for rule base. Artificial neural networks method has powerful learning ability and can approximate any function. ANFIS combines the features of two methods into one method. ANFIS can assign all possible rules according to the structure created for the problem dealt with, or allows the rules to be assigned by the expert with the help of the data. An ANFIS structure of Sugeno type is illustrated in Fig. 5 for two inputs and one output. Only two if-then rules have been shown in the figure to simplify the explanation and the rules are considered [17]:

Rule 1: if x is A1 and y is B1 then f1 = p1 * x + q1 * y + r1 (1)

Rule 2: if x is A2 and y is B2 then f1 = p2 * x + q2 * y + r2 (2)

where x and y are the inputs and p, q and r are the parameters. ANFIS structure has five layers. The inputs and outputs of each layer are indicated by arrows. Each square and circle shape is called as a node. While each square node has parameters, there is not any parameter in circle nodes. The operations performed on each layer are explained.

Layer 1: Each node in this layer is a square node and the square node function is as follows:

$$O_i^1 = \mu_{Ai}(x), \; i=1,2 \tag{3}$$

i is the node number, Ai is the linguistic label (small, middle, big), O_i^1 is the membership function of Ai. In this study, triangular membership function is considered with maximum equal to 1 and minimum equal to 0, such as

$$\mu_{Ai}(x) = \begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ \frac{c-x}{c-b}, & b \le x \le c \\ 0, & c \le x \end{cases} \tag{4}$$

Triangular is a function of x and depends a, b and c parameters. In this layer a, b and c parameters are determined and these parameters are named as premise parameters. In every loop, parameters are recalculated according to output error.

Layer 2: This layer is known as rule base layer. Every node in this layer is a circle node and labelled π. These nodes represent number of rules generated according to the Sugeno fuzzy logic system. Each node multiples the incoming signals and send them to the next layer.

$$w_i = \mu A_i(x) \text{ x } \mu B_i(y), \; i=1,2 \tag{5}$$

Layer 3: This layer is known as normalization layer. In this layer every node is a circle node and labelled N. The output of the ith node is divided by the sum of the firing outputs of all the nodes.

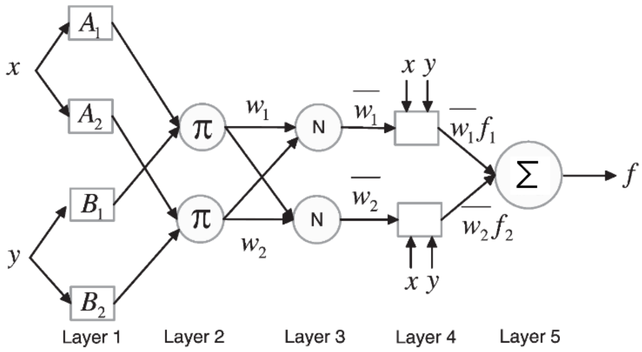

Fig. 5. ANFIS structure

$$\overline{w}_i = \frac{wi}{w1 + w2}, \; i=1, 2 \tag{6}$$

It takes all nodes coming from the previous layer as an input value and calculates the normalized value of each rule.

Layer 4: Parameters of this layer are named consequent parameters. In this layer every node is a square node and node function is expressed as follows:

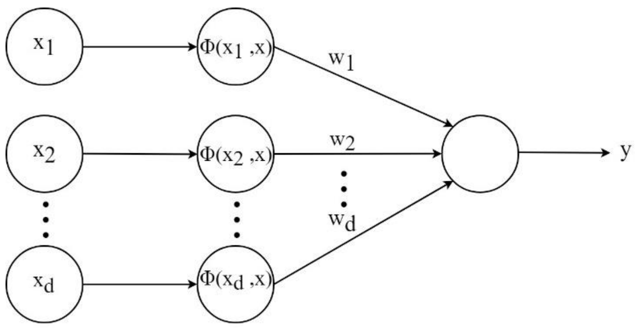

Fig. 6. SVR structure

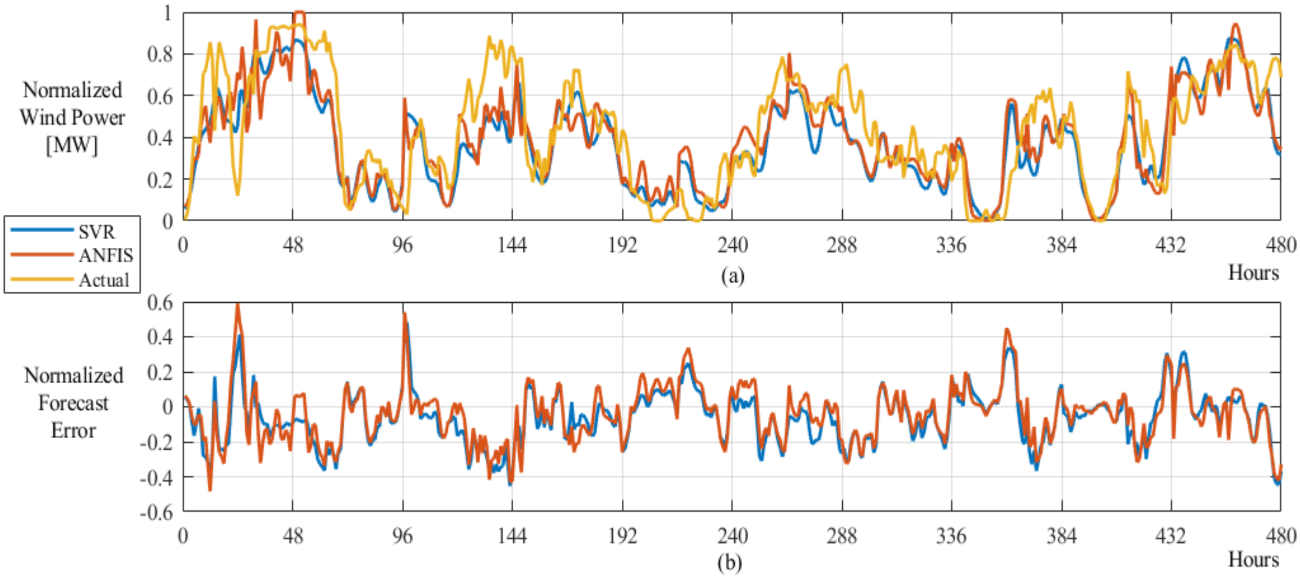

Fig. 7. (a) Actual and forecast values of 20 days for WPP 1 (b) Forecast error

$$O_i^4 = \bar{w}_i f_i = \bar{w}_I (p_i * x + q_i * y + r_i) \quad (7)$$

Layer 5: This layer is known as total layer. In this layer, there is only one circle node and this node is labelled ∑. Real output value of ANFIS system is obtained by summing the output values of the previous layer [17].

$$O_i^5 = \sum_i \bar{w} = \frac{\sum_i \bar{w}_i f_i}{\sum_i \bar{w}_i} \quad (8)$$

The used parameters are given in Table 1.

3.2. Support Vector Regression (SVR)

Support Vector Machines (SVM) developed by Vapnik in 1998 is a classification-based learning algorithm [18]. This method is much preferred in classification problems because of its performance and ability to solve the problems compared to other traditional learning methods. SVM is used for regression problems and this is named as SVR [19]. SVR is a kernel based approach and has been used successfully to solve the nonlinear problems. In this method, a nonlinear kernel transformation formula is applied to map the inputs into a feature space. Thus, the relation between the inputs and output are made linearized in the transformed space [10].

$$y = w\,\Phi(x) + b \quad (\Phi : R_n \rightarrow R_N) \quad (9)$$

Where $x \in R_n$ is the input, $y \in R_N$ is the output, b is the bias term, $w \in R_N$ is the coefficient vector and Φ is the mapping function which convert the input to a high-dimensional vector. Fig. 6. shows the structure of SVM [10].

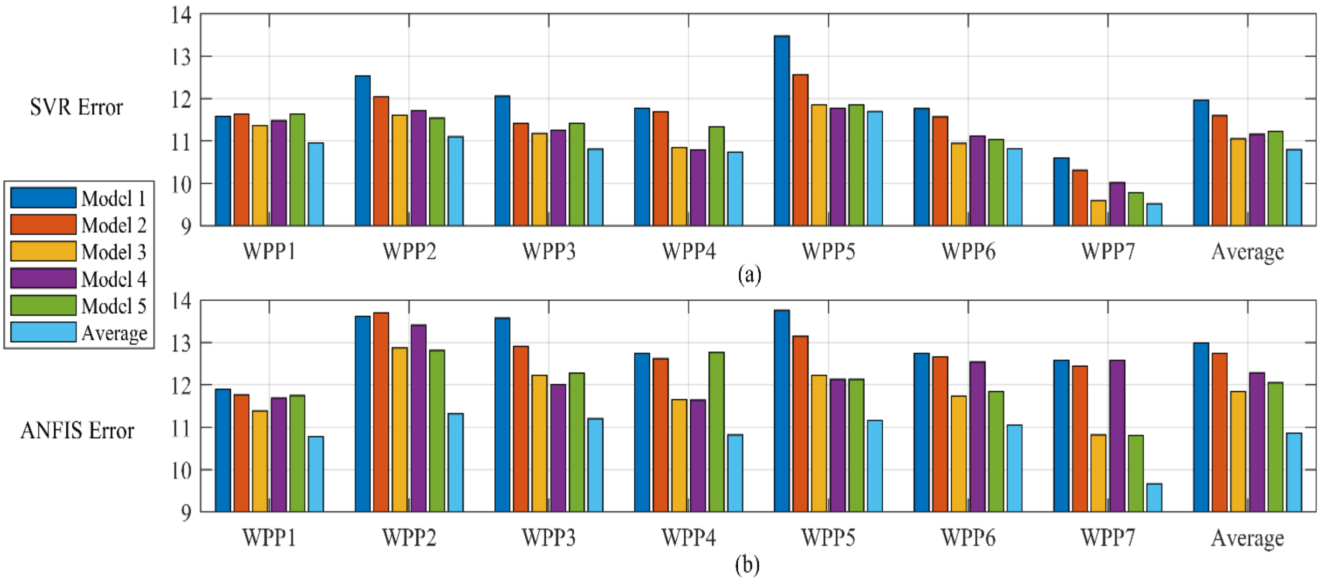

Fig. 8. (a) SVR forecast error (b) ANFIS forecast error

Table 1. The parameters of ANFIS structure

Model	Type of membership function	Number of membership functions
ANFIS 1	Triangular	3, 2 ,3
ANFIS 2	Gaussian	3, 2, 2
ANFIS 3	Triangular	3, 2, 2
ANFIS 4	Triangular	3, 2, 3
ANFIS 5	Triangular	2, 2, 3

4. Forecast Results

In literature, there are some methods for wind power forecasting error. Generally, in wind power forecasting studies Normalized Mean Absolute Percentage Error (MAPE) is not preferred, because generated wind power can be zero. In this study, Normalized Mean Absolute Error (NMAE) is selected to measure the accuracy. NMAE is defined as follows [20]:

$$NMAE = \frac{\frac{1}{n}\sum_{i=1}^{n}|r_i - f_i|}{C} \, x \, 100 \qquad (10)$$

Where i is the hour, n is number of samples, r is the real generated wind power, f is the forecasted wind power value and C is the installed wind power capacity. The normalized values calculated by dividing MAE to installed wind power capacity. Therefore, the error values of the wind power forecasts studies are easily comparable independently of the capacity of the WPP.

While ANFIS NMAE values are given in Table 2, NMAE values can be seen for SVR in Table 3. Final forecasts have lower than forecasts of models for each WPP's by looking the error rates for both methods. According to the ANFIS results, while the lowest error is found as 10.81 by using Model 5 for WPP7, the highest error is found as 13.76 by using Model 1 for WPP5. For SVR results, while the lowest error is found as 9.6 by using Model 3 for WPP7, the highest error is found as 13.47 by using Model 1 for WPP5. When the average of the model results is taken into consideration, WPP7 has the lowest error with 9.76 and WPP2 has the highest error with 11.32 for ANFIS method. In the average errors of SVR method, the lowest and highest error values are calculated as 9.52 and 11.7 respectively for WPP7 and WPP5.

Table 2. The NMAE values of ANFIS

Plant	ANFIS 1	ANFIS 2	ANFIS 3	ANFIS 4	ANFIS 5	Average
WPP 1	11.90	11.77	11.39	11.69	11.75	10.78
WPP 2	13.61	13.70	12.87	13.41	12.81	11.32
WPP 3	13.57	12.91	12.23	12.01	12.27	11.2
WPP 4	12.75	12.62	11.65	11.64	12.76	10.82
WPP 5	13.76	13.14	12.23	12.13	12.13	11.16
WPP 6	12.74	12.66	11.74	12.54	11.85	11.05
WPP 7	12.58	12.44	10.82	12.58	10.81	9.67
Average	12.99	12.75	11.85	12.29	12.05	10.86

Table 3. The NMAE values of SVR

Plant	SVR 1	SVR 2	SVR 3	SVR 4	SVR 5	Average
WPP 1	11.58	11.64	11.37	11.48	11.63	10.95
WPP 2	12.53	12.04	11.61	11.72	11.54	11.1
WPP 3	12.06	11.41	11.18	11.25	11.42	10.81
WPP 4	11.77	11.68	10.85	10.79	11.34	10.74
WPP 5	13.47	12.57	11.85	11.78	11.85	11.7
WPP 6	11.76	11.57	10.94	11.12	11.03	10.82
WPP 7	10.6	10.31	9.6	10.02	9.78	9.52
Average	11.96	11.60	11.05	11.16	11.22	10.8

While ANFIS has better results than SVR for WPP1 and WPP5, SVR has better results than ANFIS for the other five WPPs by considering average error rates. Final NMAE values of WPPs are calculated as 10.86 and 10.8 for ANFIS and SVR methods, respectively.

In Fig. 7 actual and forecast values of 20 days for WPP 1 are given with the forecast errors. Although the error differences between the methods are not much, SVR has more successful forecast results than ANFIS. It is seen that the main factor in decreasing the estimation error is to take the average by using different models rather than using two different methods. Error values of all power plants and models are shown in Fig. 8.

5. Conclusion

This paper presents a day ahead wind power forecasting in hourly bases. The proposed forecasting system consists of three stages and uses ANFIS and SVR methods. The forecasted hour, wind seed forecast and wind direction forecast are selected as system inputs. In the first stage, five different models are formed by using the system inputs in different configurations. Secondly five different ANFIS structures and SVM structures are created for each models. In the last stage, the outputs of ANFIS structures and SVR structures are averaged. Forecasts of ANFIS structures and SVR structures forecasts are compared. Although the error differences between the methods are not much, SVR has more successful forecast results than ANFIS. Proposed forecast model can perform satisfactory forecast with least error and can be an effective tool for short term wind power forecast by looking the forecast error rates.

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