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A Comparison of Support Vector Regression and Multivariable Grey Model for Short-Term Wind Speed Forecasting

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A B S T R A C T

Wind energy is one of the most promising resources of energy for the future. Wind is generally regarded as the most renewable and green energy type. The reason for this perception is mainly because of wind's inexhaustible, sustainable and abundant characteristics. Recent years has witnessed a significant increase in wind energy investments. Wind speed forecasting is considered as the most important area of research with regard to better investment and planning decisions. In this study; support vector regression and multi-variable grey model with parameter optimization are applied to the wind speed forecasting problem. The main objective of this study is to reveal the possible usage and compare the performances of support vector regression against grey theory based forecasting. The performances of the selected algorithms are benchmarked on a sample dataset. The data was obtained from Cukurova region of Turkey. Experimental results indicate that multivariable grey model with parameter optimization outperforms support vector regression in terms of forecast accuracy.

1. Introduction

Wind energy is one of the promising resources of energy for the future. Wind is generally regarded as the most renewable and green energy type. The reason for this perception is because of wind's inexhaustible, sustainable and abundant characteristics. Recent years has witnessed a significant increase in wind energy investments. As a result, it is desired to exploit wind energy as alone or hybrid, integrating to conventional sourced power systems. On the other hand, utilizing from wind brings some problems. In literature, the most subjected ones of these problems are stability and reliability, and so integration procedures. Its main reason is the uncertain and intermittent structure of wind power. The time-dependent variations of wind speed cannot harmonize the power demand schedules of today. This situation turns into problems in many areas from the management of wind power generation to reliability of wind power systems. To increase the share of wind energy in power generation, the studies should be concentrated for a good integration process and, afterwards, system reliability.

Wind is a result of many complex relations among natural events and natural structures. Therefore wind speed depends on many different parameters like temperature, air pressure etc. This complex nature of wind speed makes it hard to predict. But wind speed prediction is closely related to the power generation prediction. Thus generation and distribution planning requires accurate wind speed and power predictions. Recent progresses have made wind speed forecasting (WSF) to appear as an important area of study. There is a cubic relationship between wind speed and wind power output, so any miscalculation in WSF lead to much more deviation in power output. Thus, the most important performance criterion of WSF is accuracy.

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Usage of wind speed as a source of energy is escalated in the recent years. In this context predicting the wind speed for the current wind farms and also to analyse the feasibility of the new construction sites is becoming obligatory.

WSF methods are classified with different points of views. Generally, one can classify these as physical forecasting methods, statistical forecasting methods and hybrid approaches. Physical methods, which consider physical conditions like humidity, temperature or pressure, do not use historical data sets frequently. Statistical methods use historical data and statistical and mathematical techniques. Heuristic methods, machine learning methods, fuzzy approaches, and conventional approaches like ARIMA are mentioned under this heading [1].

2. An Overview of Wind Speed Forecasting Literature

WSF has started to pervade as a research area and scientific studies have started to be published with several approaches from different countries since 1990's. Regarding recent past, there were quite remarkable studies. Kamal and Jafri performed a stochastic simulation to forecast hourly average wind speeds by using ARMA [2]. Alexiadis et al. used Artificial Neural Networks (ANN) models and did short-term forecasting; 10-min and 1-h average values [3]. Aksoy et al. considered WSF in an aspect of civil engineering. They used wavelet transform to clean data from noise; AR models and first-order Markov chains to generate forecasts. They concluded that wavelet method always precipitates best results for forecasting of hourly mean wind speed data [4]. In 2007, Barbounis and Theocharis proposed a hybrid model, which contains local recurrent neural networks and for training stage online learning algorithms based on the recursive prediction error, to do WSF for wind farms [5].

When we look at today's studies, forecast methods are more diversified. It can be easily said that researchers have preferred to use hybrid approaches for WSF in last years. Another obtained result from literature survey is that data pre-processing have come into prominence. Seasonal adjustment methods, wavelet transform, signal decomposition algorithms and empirical mode decomposition are data pre-processing methods using commonly.

When we regard to forecasting stage; the conventional statistical methods, of course, are still in use; e.g. AR, ARMA, ARIMA and versions of these. The studies of [6], [7] and [8] are given as examples of using conventional methods.

On the other hand, usage of modern forecasting methods is on the rise – mostly metaheuristics. [9], [10], [11], [12], [13], [14], [15] and [16] are some examples of studies used metaheuristics for WSF.

If we look for grey theory studies, there are few studies again. In [17] grey related weighted combination was applied to monthly average wind speed data for monthly forecasts. In [16], a different hybrid approach with metaheuristics and grey relational analysis was proposed for the analysis of daily wind speed series. As a result, we are able to conclude that there is no study in literature in which machine learning and grey theory are used together after wavelet transformation process for WSF. So, this situation contributes originality to our study in terms of using methods.

Considering recent studies, it can be seen that there are few studies using our approaches. Jiang et al. proposed a hybrid method for WSF which consists of grey correlation and v-support vector machine in 2017. They aimed to reduce the effects of the model parameters on the results [18]. Lahouar and Slama used random forests for hour-ahead wind power forecasting. They obtained a dramatic improvement in forecast results compared to classical neural network prediction [19]. Men et al. used an ensemble of mixture density neural networks for short-term WSF. To determine the distribution of wind speed random variable, a mixture of Gaussian distributions was used. The proposed approach worked well on a case study from a wind farm in Taiwan [20]. The Gaussian process was also exploited for short-term WSF. A hybrid model was proposed in the paper which consists of the Empirical Wavelet Transform, Expectation Propagation algorithm and Gaussian process regression with the Student-t Observation Model [21]. As a final example, Chang et al. proposed an improved radial basis function neural network-based model in which an additional shape parameter from classical Gaussian basis function also takes part [22].

WSF is also sorted into categories based on the time scale of predictions. In brief, the very short-term (seconds to a few minutes) wind speed forecasting aims to predict instantaneous change in the wind speed to sustain operational activities and real-time operations of the electricity market. Short-term (up to 2 days) forecasting is used in the control of wind turbines, economic dispatch planning, unit commitment and operational security of the market; medium-term (up to 1 week) forecasting is for operation & maintenance planning and management and optimizing operating costs; and long-term (monthly, seasonal, annual) forecasting is for wind power plant design and investment decisions [15]. We see in our literature survey that the tendency is directed to short-term studies, the greatest majority of papers contains short-term WSF. The developments in power markets, such that pervading of real-time markets require short-term forecasts as soon as possible.

Another considerable parameter of WSF researches is the data type. Aside from wind speed, several physical indicators may use which affect wind speed indirectly. In this type of studies, mostly, both wind speed and temperature data are analysed together. Besides, air pressure, humidity, rainfall data are examples of other physical data types.

Based on the above literature review, we have formed a frame for our paper. Both grey prediction and support vector regression will be used in this study. Furthermore, a very short-term WSF will be performed which forecasts 15 minutes ahead wind speed. Our aim is to compare the performances of support vector regression and grey theory-based prediction algorithms among each other. The models use historical wind speed and temperature data. A time series model is generated and employed to build and train the prediction methods.

3. Forecasting Algorithms

3.1. Support vector regression

SVM is especially suitable for solving problems of small sample size [23]. SVM is grounded in the framework of statistical learning theory, which has been developed by Vapnik and Chervonenkis in 1974. SVR maps the input data x into a higher dimensional feature space through a nonlinear mapping Φ and then a linear regression problem is obtained and solved in this feature space [24]. With the given training data $\{(x_1,y_1),\ldots,(x_i,y_i),\ldots,(x_n,y_n)\}$, the mapping function can be formulated as;

$$f(x)=\sum_{i=1}^{n}\omega_i\phi_i x_i+b \tag{1}$$

where ω_i and b are the parameters that need to be defined. SVR has to find a function $f(x)$ that has at most ε deviation from the actually obtained targets y_i for all the training data and at the same time is as flat as possible. Flatness, in this case, means to reduce the model complexity by minimizing $\|\omega\|^2$, so that this problem can be written as an optimization problem;

$$\begin{aligned}&Min\frac{1}{2}\|\omega\|^2\\ &s.t\begin{cases}y_i-\Phi(\omega,x_i)-b\le\varepsilon\\ \Phi(\omega,x_i)+b_i-y\le\varepsilon\end{cases}\end{aligned} \tag{2}$$

Formula 2 defines a constrained optimization problem. Formula 3 shows the solution of this problem.

$$\begin{aligned}&Max\ W(\alpha)=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i=1,j=1}^{n}\alpha_i\alpha_j y_i y_j x_i^T x_j\\ &\qquad\text{s.t. } C\ge\alpha_i\ge 0,\ \sum_{i=1}^{n}\alpha_i y_i=0\end{aligned} \tag{3}$$

3.2. Multi-variable grey prediction model with parameter optimization

Grey Theory, extremely high mathematical analysis of the systems that are partly known and partly unknown and defined as ‘‘weak knowledge’’ and ‘‘insufficient data’’, was first introduced by Ju-Long [25]. Grey prediction is one of the most important parts in the grey theory. Grey prediction models have been used in many problems. The GM(1, N) model, which provides good prediction using limited data, is the basic multi-variable grey prediction model. GM(1, N) indicates N variable and one order grey forecasting model. The calculation steps of GM(1, N) model are described as follows [26; 27]:

Step 1: Assume $X_i^{(0)}=\{x_i^{(0)}(1),x_i^{(0)}(2),\ldots,x_i^{(0)}(n)\}$ be an original sequence of variable i. For i=1, this sequence includes output values of the data set, the others contain input data sets.

Step 2: For each input data set and output data set, new sequences $X_i^{(1)}$ are generated using accumulated generating operation (AGO).

$$X_i^{(1)}=\{x_i^{(1)}(1),x_i^{(1)}(2),\ldots,x_i^{(1)}(n)\} \tag{4}$$

$$x_i^{(1)}(k)=\sum_{j=1}^{k}x_i^{(0)}(j) \tag{5}$$

Step 3: A sequence $Z^{(1)}=\{z^{(1)}(2),\ldots,z^{(1)}(i),\ldots,z^{(1)}(n)\}$ is obtained by consecutive values of sequence $X_1^{(1)}$.

$$z^{(1)}(k)=\alpha x_1^{(1)}(k)+(1-\alpha)x_1^{(1)}(k-1),\qquad \forall k=2,3,\ldots,n,\ \ 0\le\alpha\le 1 \tag{6}$$

Step 4: The first-order multi-variables grey differential equation of GM(1, N) is established as follows [27]:

$$x_1^{(0)}(k)+\mathrm{a}z_1^{(1)}(k)=\sum_{j=2}^{N}b_jx_j^{(1)}(k)=b_2x_2^{(1)}(k)+b_3x_3^{(1)}(k)+\ldots+b_Nx_N^{(1)}(k) \tag{7}$$

In this equation, parameters $a, b_2, b_3, \ldots, b_N$ can be calculated as follows using the least square method.

$$\left[a,b_2,b_3,\ldots,b_N\right]^T=(B^TB)^{-1}B^TY \tag{8}$$

where

$$Y=\left[x_1^{(0)}(2)\quad x_1^{(0)}(3)\quad \ldots\quad x_1^{(0)}(n)\right]^T \tag{9}$$

$$B=\begin{bmatrix}-z^{(1)}(2) & -x_2^{(1)}(2) & \cdots & -x_N^{(1)}(2)\\ -z^{(1)}(3) & -x_2^{(1)}(3) & \cdots & -x_N^{(1)}(3)\\ \vdots & \vdots & \vdots & \vdots\\ -z^{(1)}(n) & -x_2^{(1)}(n) & \cdots & -x_N^{(1)}(n)\end{bmatrix} \tag{10}$$

Step 5: The predicted values of the accumulated sequence are obtained using following equation.

$$\hat{x}_1^{(1)}(k+1)=(x_1^{(0)}(1)-\sum_{i=2}^{N}\frac{b_i}{a}x_i^{(1)}(k+1))\,\mathrm{e}^{-ak}+\sum_{i=2}^{N}\frac{b_i}{a}x_i^{(1)}(k+1) \tag{11}$$

Step 6: The predicted values of the original sequence are calculated by using the inverse accumulated generating operation (IAGO).

$$\hat{x}_1^{(0)}(k+1)=\hat{x}_1^{(1)}(k+1)-\hat{x}_1^{(1)}(k)\quad k\ge 2 \tag{12}$$

Traditional GM(1, N) model often sets the parameter α to 0.5. This value is not optimal for all datasets. Therefore, in this study, in order to improve the forecast performance of the original GM(1, N) model, genetic algorithms can be used to optimize the parameters of this model. To this end, the following model is established.

$$\min\quad Z=\frac{1}{n}\sum_{k=1}^{n}\left|\frac{\hat{x}_0(k)-x_0(k)}{x_0(k)}\right| \tag{13}$$

$$0\le\alpha\le 1 \tag{14}$$

where $x_0(k)$ is the actual value, $\hat{x}_0(k)$ is predicted value and n is the number of sequence data.

4. Forecasting Process

In this study, very short-term wind speed is to be forecasted. At each time period, lagged wind speed data, month, hour, week number, minimum and maximum temperature data is used for training. Then, this model is used to predict the wind speed of the next period. It is important to emphasize again that each period's wind speed is predicted by using the values up to the current point. As each period passes, the training data grows to include the last period's data to improve the model training performance. Therefore, a new model is trained at the beginning of each period.

4.1. Model description

A time series data vector is used with a predetermined lag structure. If t is the timestamp of the current period, and T is the forecast interval, a time series model for the prediction of $t+T$ is constructed as in formula 15.

$$\hat{y}(t+T)=f(y(t),y(t-T),\ldots,y(t,nT)) \tag{15}$$

Here $\hat{y}(t+T)$ is the prediction and $y(t), y(t-T),....,y(t,nT)$ are observed values of past n periods. Apart from the historical wind speed data, additional variables are also included to build the time series model $f(.)$. These are minimum and maximum temperature values (P^{min}, P^{max}) of the current time period, month number (M_t), week number (W_t), hour (h_t) current wind direction (D_t) and rain status (R_t) of the current time period. A numerical value is assigned to each wind direction category in the raw dataset. Rain status is indicated with the amount of average rain drop to per square meter. The final model is given in formula 16.

$$\hat{y}(t+T) = f(y(t), y(t-T),....,y(t,nT), P^{\min}(t), P^{\max}(t), M(t), W(t), h(t), D(t), R(t)) \tag{16}$$

Root mean squared error (RMSE) and mean absolute percentage error (MAPE) is employed as the performance metric. The formulas for RMSE and MAPE are given in Formula 17 and Formula 18 respectively. Where y_i is the observed and $\hat{y}_i$ is the predicted value and n is the number of instances predicted in the dataset.

$$RMSE = \sqrt{(\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{17}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\left|\frac{y_i - \hat{y}_i}{y_i}\right|\right) \times 100\% \tag{18}$$

5. Experimental Study

The performances of the selected algorithms are benchmarked on a sample dataset. The data was obtained from Cukurova region of Turkey. The original data was recorded in 15 minutes intervals between the years 2009 and 2011. This leads to 75325 instances in the dataset. The collected data includes the timestamp, minimum and maximum temperatures, humidity, wind direction, rain information and the wind speed values. A sample of the dataset can be seen in Table 1.

Table 1. Sample rows from the data set

Year	Month	Day	Hour	Minute	# of Week	Highest Temperature	Lowest Temperature	Direction	Rain	Wind Speed
2011	1	1	0	0	1	13.6	13.1	2	0	0.9
2011	1	1	0	15	1	13.6	13.4	2	0	0.9
2011	1	1	0	30	1	13.4	13.2	2	0	0.9
2011	1	1	0	45	1	13.7	13.3	2	0.3	1.3
2011	1	1	1	0	1	13.5	13.3	3	0.8	0.9

5.1. Parameter selection

It is expected that in a regression model some of the possible input variables may have more importance on the target estimation parameter. To analyze the importance of the selected input variables, a time series model with a lag value of 6 is employed. Predictor importance estimates are calculated. For each variable, the increase in the prediction error if the values of the variable are permuted across the out-of-bag observations are computed on every tree. Then, the average over the entire ensemble is calculated and divided by the standard deviation over the entire ensemble. Calculated metric values can be seen in Table 2. Also, Figure 1 shows the predictor importance of the selected parameters on a bar chart.

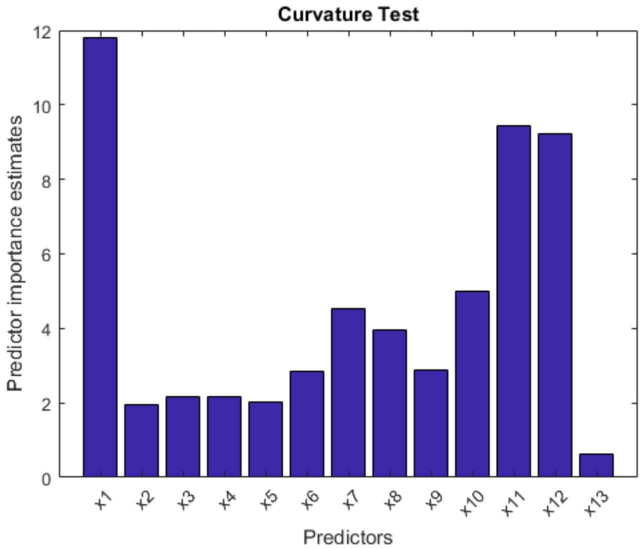

Figure 1. Bar chart of the parameters' importance metric values

Average value of the calculated importance metrics of the selected parameters is chosen as the threshold, which is 4.5. Based on this threshold, the parameters $y(t\text{-}1)$, P^{min}, W_t, h_t and D_t are selected as inputs to the model.

Chained cross-validation approach is used to analyse the prediction performance of the selected algorithms. At the first step %50 of the dataset is used to train the model and then this trained model is employed to make a prediction for the next %5 part of the dataset. In the second step, the test part of the first step is also added to the training dataset and the next %5 is predicted with the trained model. This approach is repeated until the end of the dataset is reached.

Table 2. Importance metric values of the parameters in the data set

Variable		Importance Metric
X_1	$y(t-1)$	11.811
X_2	$y(t-2)$	1.941
X_3	$y(t-3)$	2.178
X_4	$y(t-4)$	2.183
X_5	$y(t-5)$	2.028
X_6	$y(t-6)$	2.852
X_7	$P^{\min}$	4.514
X_8	$P^{\max}$	3.941
X_9	M_t	2.878
X_{10}	W_t	4.990
x_{11}	h_t	9.433
x_{12}	D_t	9.237
x_{13}	R_t	0.643

Proposed forecasting algorithms are programmed in MATLAB 2016b. For support vector regression Gaussian kernel is selected. In the multivariable grey model with parameter optimization, the parameter values of the genetic algorithm are as follows: the population size is 40, the crossover rate and mutation rate is set to be 0.9 and 0.05 respectively. The default values of the MATLAB optimization toolbox are used for the other parameters such as stopping criteria, elite count and selection function. The RMSE and MAPE values of the original GM(1, N) model are 0.9245 and 63.16%, respectively. In the GM(1, N) with parameter optimization, the minimum MAPE (25.63%) and RMSE 0.4175 are obtained by using the genetic algorithm. The numerical results show that the parameter optimization significantly increases the original GM(1, N) model's performance. The proposed grey model presents an efficient methodology for short-term wind speed forecasting.

Table 3. Performance of the selected algorithms

Method	MAPE
Support Vector Regression	0.2977
GM(1,N) with parameter optimization	0.2563

6. Results and Conclusion

In this paper, support vector regression and multivariable grey model are benchmarked on a large sample data for short-term wind speed forecasting. Among the many variables present in the dataset, a predictor importance analyze is conducted and previous period's wind speed, minimum temperature, week number, hour and wind direction are selected as the model parameters. This analysis showed that older-than-one-period historical wind speed data is not effective on forecasting performance. Also, rain information and the maximum temperature had negligible effect. A chained cross-validation procedure is applied and the results are reported. The results indicated that multivariable grey model with parameter optimization achieved better results than the support vector regression on the dataset.

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