INFORMATICA, 2015, Vol. 26, No. 3, 493–508

DOI: http://dx.doi.org/10.15388/Informatica.2015.60

Sensorless Estimation of Wind Speed by Soft Computing Methodologies: A Comparative Study

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Received: November 2013; accepted: January 2015

Abstract. This paper shows a few novel calculations for wind speed estimation, which is focused around soft computing. The inputs of to the estimators are picked as the wind turbine power coefficient, rotational rate and blade pitch angle. Polynomial and radial basis function (RBF) are applied as the kernel function of Support Vector Regression (SVR) technique to estimate the wind speed in this study. Instead of minimizing the observed training error, SVR_poly and SVR_rbf attempt to minimize the generalization error bound so as to achieve generalized performance. The results are compared with the adaptive neuro-fuzzy (ANFIS) results.

Key words: wind pace, wind turbine, ANFIS, support vector regression, soft computing.

1. Introduction

Because of natural issue and absence of force renewable energy has gotten much consideration. Wind energy utilization created enormously all through the world in place of attaining the perfect of a future with ecologically natural electrical era (Celik, 2003). Then again, wind is one of the climate variables that are very difficult to measure and to predict (Tamuraa *et al.*, 2001; Wachter *et al.*, 2008). Estimation of wind speed is very important in force frameworks because of the estimation the energy yield of wind speed (Kunz *et al.*, 2010; Ozgonenel and Thomas, 2012).

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Different kinds of wind power systems used variable velocity power generation framework (Song *et al.*, 2000) as more noteworthy than others because of high power extraction and high power quality (Boukhezzar and Siguerdidjane, 2009; Tian *et al.*, 2011). By using wind different speeds one should keeping in mind the end goal to attain the most extreme force of wind turbine, the turbine shaft rotational velocity ought to be adjusted ideally regarding the variable wind speed (Østergaard *et al.*, 2007). Turbine rotor rate control needs to base on the ongoing data of wind pace (Hizi *et al.*, 2008; Usta and Kantar, 2012). Ordinarily, anemometers are committed for the wind speed measurements. On the other hand, high cost of the anemometers limits the significant utilization of this mechanical assembly. Case in point, the encompassed introduced anemometers can't give respectable and exact wind speed data for each wind turbine in wind ranches (Leea *et al.*, 2012). The mounted anemometer on the highest point of nacelle may be a cause of wrong estimation of the wind speed (Sozzi *et al.*, 2001). In wind cultivates, a few anemometers are regularly set at a few positions to gauge the normal wind speed (Pandey, 2002). The utilization of anemometers supports an issue of conformity and estimation exactness, and also expanding the beginning expense of the wind era frameworks (Diniz *et al.*, 2004). Consequently, it is attractive to supplant the mechanical anemometers by the computerized wind-speed estimator focused around the turbine trait (Kusiak and Li, 2010; Abo-Khalil and Lee, 2008). As of late, the wind-speed estimation techniques have been accounted for in the writing (Lopez *et al.*, 2008; Qin *et al.*, 2011; Carro-Calvo *et al.*, 2011; Mohandes *et al.*, 2011; An and Pandey, 2005; Lombardo, 2012).

The wind speed are nonlinear power source that need accurate on-line identification for the optimal operating of the wind turbines (No *et al.*, 2009; Rocha, 2011; Meharrar *et al.*, 2012). Since it is nonlinear function a soft computing techniques are preferred for its estimation and prediction. Aiming at optimizing such systems to ensure optimal functioning of the unit, many soft computing techniques are used today such as the fuzzy logic (FL) (Qi and Meng, 2012; Bououden *et al.*, 2012), artificial neural network (ANN) (Wua *et al.*, 2013; Yilmaz and Özer, 2009), neuro-fuzzy (Mohandes *et al.*, 2011; Oguz and Guney, 2010; Meharrar *et al.*, 2011; Ata *et al.*, 2010) and support vector machines (SVM) (Lu *et al.*, 2006; Leng *et al.*, 2013; Adankon and Cheriet, 2011). The essential thought behind the soft computing approach is to gather data/yield information sets and to take in the proposed system from these information.

Artificial neural networks (ANNs) are in effect broadly connected to different zones to beat the issue of nonlinear connections and expectations (Sedighizadeh and Rezazadeh, 2008; Petković *et al.*, 2013a; Barlas and Kuik, 2005; Kassem, 2012; Li *et al.*, 2005). Support Vector Machines (SVMs), as another type of soft computing methods, has picked up criticalness in determining issues identified with environment (Ornella and Tapia, 2010; Jain *et al.*, 2009; Lieber *et al.*, 2013; Qi *et al.*, 2013). There are two main categories for support vector machines: support vector classification (SVC) and support vector regression (SVR). SVM is a learning system using a high dimensional feature space (Ananthakrishnan *et al.*, 2013; Ye *et al.*, 2009; Balahura and Turchi, 2014; Chakraborty, 2011; Zhao and Liu, 2007). The Support Vector Regression calculations (SVR) particularly created for regression issues are engaging calculations for an expansive assortment of regression issues, since they don't just consider the error approximation to the information, additionally the speculation of the model, i.e., their capacity to enhance the forecast of the model when new information are assessed by it (Rajasekaran *et al.*, 2011; Yang *et al.*, 2009; Liu *et al.*, 2013; Ortiz-García *et al.*, 2010; Jiang and He, 2012; Yan *et al.*, 2011; Tang *et al.*, 2009). SVR is focused around statistical learning theory and a structural risk minimization, which has been effectively utilized for nonlinear framework displaying (Wei *et al.*, 2013; Zhang *et al.*, 2013; Wu *et al.*, 2004; Bermolen and Rossi, 2009; Basak *et al.*, 2007). The exactness of a SVM model is to a great extent subject to the choice of the model parameters. Be that as it may, organized systems for selecting parameters are needing. Hence, a model parameter alignment ought to be made.

Two SVR schemes for the sensorless determination of wind speed were investigated in this article. The first SVR scheme is radial basis function (SVR_rbf) and the next is polynomial function (SVR_poly). These are kernel functions which are used to form function for SVM. Adaptive neuro-fuzzy inference system (ANFIS) (Jang, 1993; Petković and Pavlović, 2013; Petković *et al.*, 2012a, 2012b; Petković and Ćojbašić, 2012; Petković *et al.*, 2013b, 2013c, 2013d) was also investigated. The chief goal of this article is to establish the soft computing techniques for sensorless estimation of wind speed. Those systems should be able to forecast the wind speed in regards to the main turbine parameters without active sensors.

2. Wind Speed Model

The essential parts of a regular wind transformation framework are wind turbine, a generator, interconnection gadgets, and control framework. Along these lines, the outline of a wind energy change framework is intricate. The most critical piece of a wind energy change framework is the wind turbine transforming the wind dynamic energy into mechanical or electric vitality. The framework essentially contains a blade, a mechanical part and an electric motor coupled to one another. The kinetic energy of wind is the capacity of wind speed, the particular mass of air, the territory of air space where the wind is caught and the stature at which the rotor is set. The force accessible in a uniform wind field can as communicated as

$$P_w = \frac{1}{2}\rho A v^3 \tag{1}$$

where P_w is the power [W] of the wind with air density ρ [kg/m^3] and wind pace v [m/s] is passing through the swept area A [m^2] of a rotor disk that is orthogonal to the wind stream. The wind turbine can just catch a share of the force accessible from the wind. The proportion of caught force to accessible force is alluded to as the force coefficient

$$C_p(\beta, V_e, \Omega_r, R) \tag{2}$$

which is a function of the blade pitch angle β, wind pace V_e, rotor speed Ω_r and rotor radius R. The value of C_p can be calculated as:

$$C_p(\beta, V_e, \Omega_r, R) = 0.5176\left(\frac{116}{\frac{1}{\frac{R\Omega_r}{V_e}-0.08\beta}-\frac{0.035}{\beta^3+1}} - 0.4\beta - 5\right)e^{\frac{-21}{\frac{1}{\frac{R\Omega_r}{V_e}-0.08\beta}-\frac{0.035}{\beta^3+1}}} + 0.0068\frac{R\Omega_r}{V_e}. \quad (3)$$

The main aim in this article is to define wind pace V_e in relation to the three parameters: blade pitch angle β, rotor speed Ω_r and power coefficient C_p for rotor radius $R = 75$ m:

$$V_e(C_p, \beta, \Omega_r). \quad (4)$$

SVR methods were used to make this correlation. According to the three parameters the SVR should determine wind speed.

3. Support Vector Regression Application

The main principle of support vector machines (SVMs) is to do the non-linear data mapping and feature space. If a way of computing the inner product in a feature space is available directly as a function to the original input points, it is possible to build a non-linear learning machine, which is known as a direct computation method of a kernel function, denoted by K.

The flexible nature of the SVM is attributed to the kernel functions that implicitly chart the data to a higher-dimensional feature space. A linear solution in the higher-dimensional feature space corresponds to a non-linear solution in the original, lower-dimensional input space. There are some available methods that employ non-linear kernels in their strategy for regression problems and that simultaneously apply SVMs. One kernel function is the radial basis function. The main benefit of the radial basis function is that it is computationally more efficient than the customary SVM method, since radial basis function training needs only the solution of a set of linear equations instead of the lengthy and computationally demanding quadratic programming problem that is entailed in standard SVM. Compared with other probable kernel features, the radial basis function is a more compressed, supported kernel, which makes it very suitable for restricting the computational training process and improving the generalization efficiency of the radial basis function – an attribute of great value in model design. Therefore, the radial basis function with parameter σ is adopted in this study. The non-linear radial basis kernel function is defined as:

$$K(x, x_i) = \exp\left(-\frac{1}{\sigma^2}\|x - x_i\|^2\right) \quad (5)$$

where x and x_i are vectors in the input space, i.e. vectors of features computed from training or test samples.

In this study the following polynomial kernel function was also used:

$$K(x, y) = \left(x^T y + c\right)^d \quad (6)$$

Table 1
Statistical properties of the training data for SVR

Wind turbine			
Input parameters	Average value	Maximum value	Minimum value
	$\bar{x}$	$(x_{\max})$	$(x_{\min})$
Rotor speed (rpm)	7.988345	13.3733	1.03275
Blade pitch angle (deg)	20.57143	45	0
Power coefficient (Cp)	0.206539	0.480012	0.069299

where x and y are vectors of features computed from training or test samples, and c is a constant making a tradeoff for the influence of higher-order versus lower-order terms in the polynomial.

As an issue driven model, the capacity of the SVR to make sensible estimations is generally subject to include parameter choice. Sufficient attention of the components controlling the framework mulled over is accordingly critical to creating a dependable system. As indicated by the tests (Petković *et al.*, 2013a), the inputs parameters (rotor speed, blade angle and power coefficient) are gathered in wind turbine and characterized as data for the learning system. The information are gathered by National Instruments DAQ card. For the analyses, 70% of the information was utilized to prepare tests and the resulting 30% served to test examples. A synopsis of the measurable properties of the wind turbine database is given in Table 1.

4. Proposed Support Vector Regression for Prediction

The three SVR models were created, namely SVR_1, SVR_2 and SVR_3. SVR_1 has two inputs: blade pitch angle and power coefficient; SVR_2 hast three inputs: blade pitch angle, rotor speed and power coefficient; SVR_3 has two inputs: blade pitch angle, rotor speed. The flowchart for the SVR model can be described as follow:

- Data acquisition.
- Creating an SVR prediction.
- Prediction of wind speed.
- Detection precision.

The estimation process by a the SVR models is shown in Fig. 1.

5. ANFIS Model

In this area, the advancement of the estimator procedure for estimation of the wind pace is displayed utilizing the ideas of ANFIS plan. The fuzzy rationale gives a calculation, which changes over the phonetic estimation, in view of master information, into a programmed estimation system. Phonetic variables, characterized as variables whose qualities are sentences in a characteristic dialect, (for example, huge or little), may be spoken to by the fuzzy sets. A fuzzy set is an augmentation of a "crisp" set where a component can just have a place with a set (full enrollment) or not have a place whatsoever (no participation).

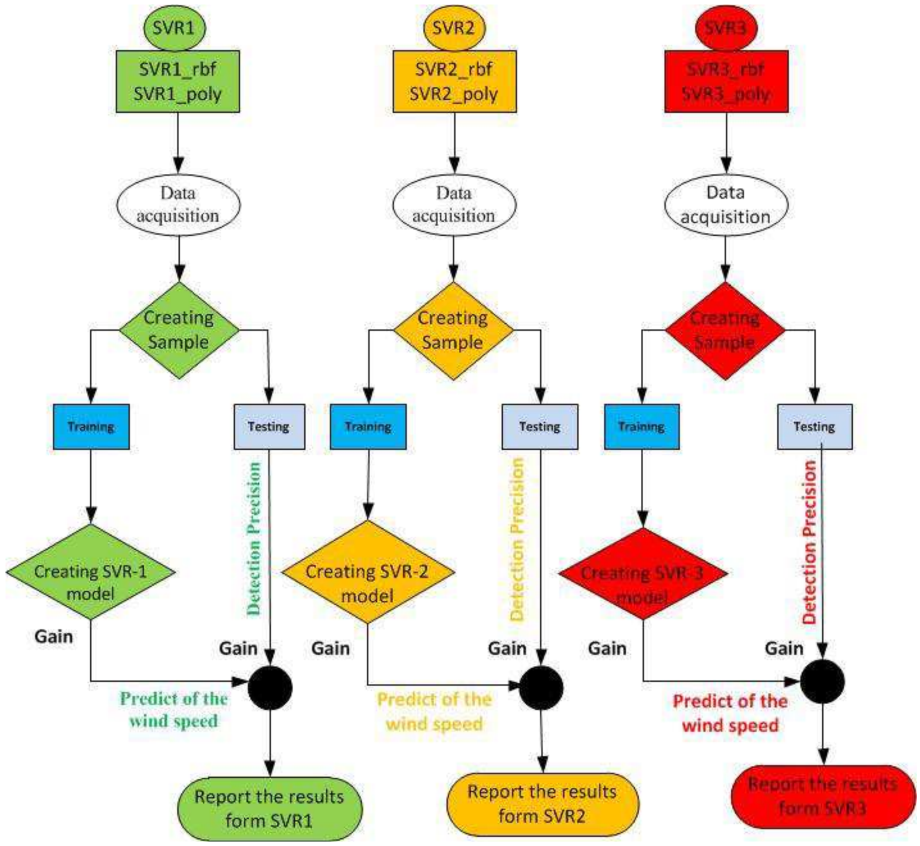


Fig. 1. The process of prediction by SVM agents.

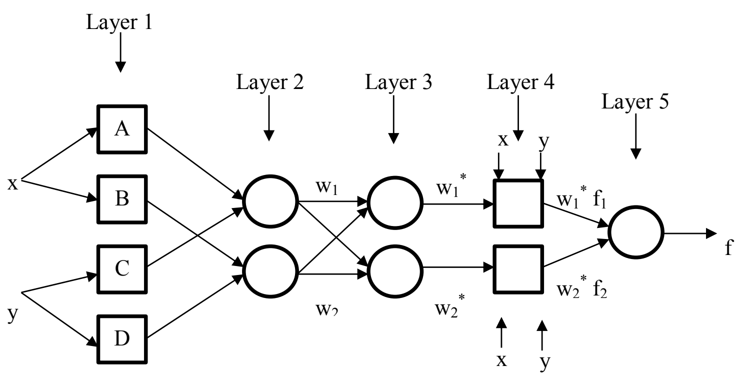


Fig. 2. ANFIS structure.

Fuzzy sets permit fractional enrollment, which implies that a component might in part fit in with more than one set.

Figure 2 shows an ANFIS structure with two inputs. According to training input/output data, the ANFIS network could estimate wind speed.

In this work, the first-order Sugeno model with two inputs and fuzzy IF-THEN controls of Takagi and Sugeno's sort is utilized:

$$\text{if } x \text{ is } A \quad \text{then } f_1 = p_1 x + t. \tag{7}$$

The main layer comprises of information membership functions (Mfs). This layer simply supplies the data qualities to the following layer. The information is compelling wind speed. In the first layer each hub is a versatile hub with a hub capacity

$$O = \mu(x, y, z),$$

where $\mu(x, y, z)_i$ are MFs.

In this study, bell-shaped function Mfs (8) with greatest equivalent to 1 and least equivalent to 0 is picked

$$f(x; a, b, c) = \frac{1}{1 + \left(\frac{x-c}{a}\right)^{2b}} \tag{8}$$

where the bell-shaped function hinges on upon three parameters a, b and c. The parameter b is typically positive.

The second layer (participation layer) checks for the weights of every Mfs. It accepts the info values from the first layer and goes about as Mfs to speak to the fuzzy sets of the individual information variables. Each hub in the second layer is non-adjustable and this layer duplicates the approaching indicators and sends the item out like

$$w_i = \mu(x)_i * \mu(x)_{i+1}. \tag{9}$$

Every hub yield speaks to the terminating quality of a guideline or weight.

The third layer is known as the tenet layer. Every hub (every neuron) in this layer performs the precondition matching of the fuzzy guidelines, i.e. they process the enactment level of each one run, the amount of layers being equivalent to the amount of fuzzy tenets. Every hub of these layers ascertains the weights which are standardized. The third layer is additionally non-versatile and each hub computes the proportion of the tenet's terminating quality to the whole of all principles' terminating qualities like

$$w_i^* = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2. \tag{10}$$

The yields of this layer are called standardized terminating strengths or standardized weights.

The fourth layer is known as the defuzzification layer and it gives the yield qualities coming about because of the deduction of standards. Each hub in the fourth layer is a versatile hub with hub capacity

$$O_i^4 = w_i^* x f = w_i^* (p_i x + q_i y + r_i) \tag{11}$$

where $\{p_i, q_i, r\}$ is the parameter situated and in this layer is alluded to as ensuing parameters.

The fifth layer is known as the yield layer which wholes up all the inputs hailing from the fourth layer and changes the fuzzy grouping outcomes into a crisp (binary). The yield speaks to evaluated tweak exchange capacity of the optical framework. The single hub in the fifth layer is not versatile and this hub figures the by and large yield as the summation of all approaching signs

$$O_i^5 = \sum_i w_i^* x f = \frac{\sum_i w_i f}{\sum_i w_i}. \tag{12}$$

The hybrid algorithm were connected to distinguish the parameters in the ANFIS architectures. In the forward pass of the cross hybrid algorithm, practical signs go ahead until Layer 4 and the resulting parameters are identified by the minimum squares gauge. In the regressive pass, the slip rates spread regressively and the reason parameters are upgraded by the gradient secent.

6. Models Performance Evaluation

To assess the success of the SVR models and ANFIS technique, some statistical indicators were examined as follows:

(1) root-mean-square error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}, \tag{13}$$

(2) coefficient of determination (R^2)

$$R^2 = \frac{\left[\sum_{i=1}^{n}(O_i - \bar{O}_i) \cdot (P_i - \bar{P}_i)\right]^2}{\sum_{i=1}^{n}(O_i - \bar{O}_i) \cdot \sum_{i=1}^{n}(P_i - \bar{P}_i)} \tag{14}$$

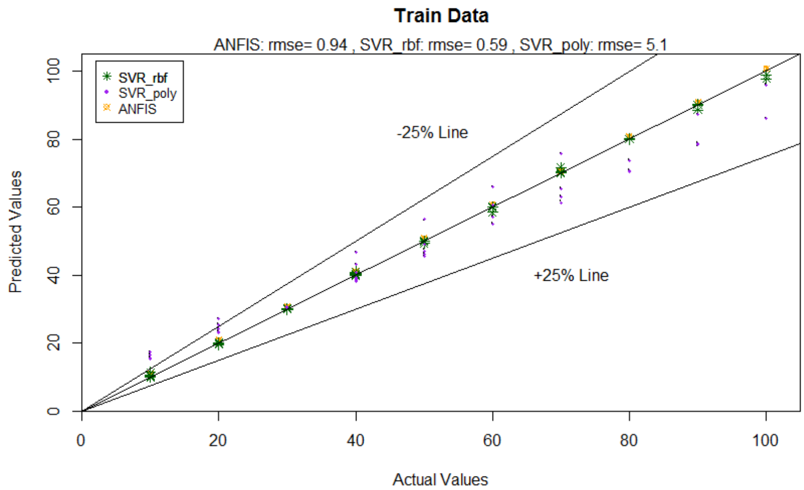
where P_i and O_i are known as the experimental and forecast values, respectively, and n is the total number of test data.

7. Results and Discussion

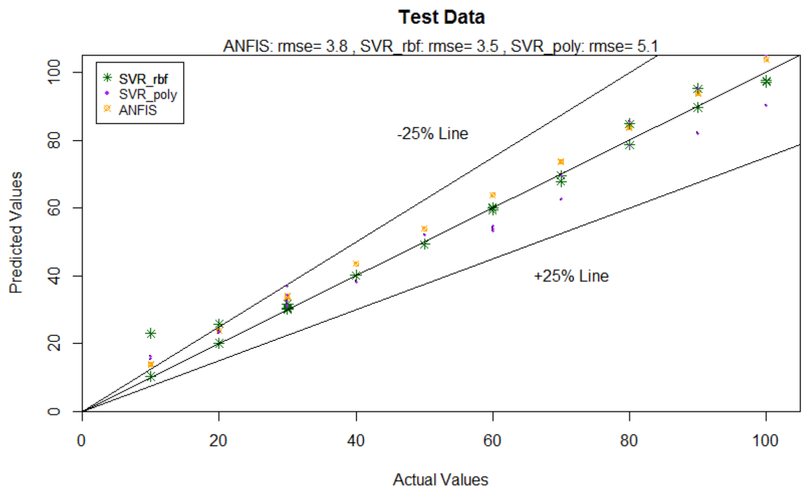
The three parameters associated with SVR kernel are C, e and r. SVM model accuracy is dependent on model parameter selection. In our scheme, a default value of $e = 0.1$ was used. To select user-defined parameters (i.e. C, d and g), a large number of trials were carried out with different combinations of C and d for polynomial kernels and C and g for radial basis function kernels. Table 2 provides the optimal values of user-defined parameters for this dataset with polynomial and RBF kernel SVR.

Table 2
User-defined parameters for SVR.

SVR_1						SVR_2						SVR_3					
SVR_rbf			SVR_poly			SVR_rbf			SVR_poly			SVR_rbf			SVR_poly		
C	*y*	*e*	*C*	*d*	*e*	*C*	*y*	*e*	*C*	*d*	*e*	*C*	*y*	*e*	*C*	*d*	*e*
3	0.01	0.001	10	1.9	0.01	3	0.01	0.001	10	1	0.01	3	0.01	0.001	10	1.9	0.01

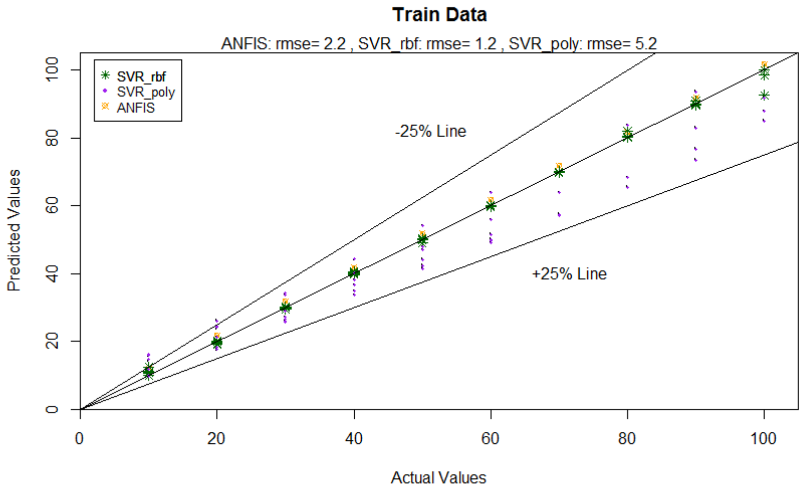


(a)

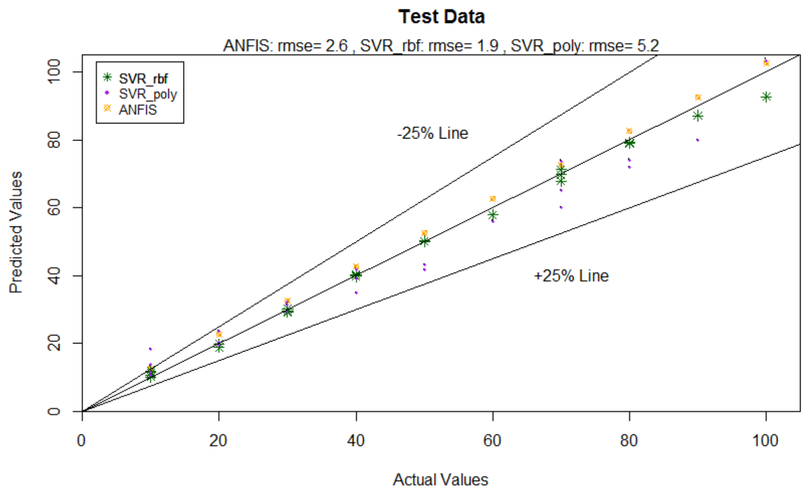


(b)

Fig. 3. Performance of SVR_rbf, SVR_poly and ANFIS on the SVR_1 case in (a) training phase and in (b) testing phase.



(a)

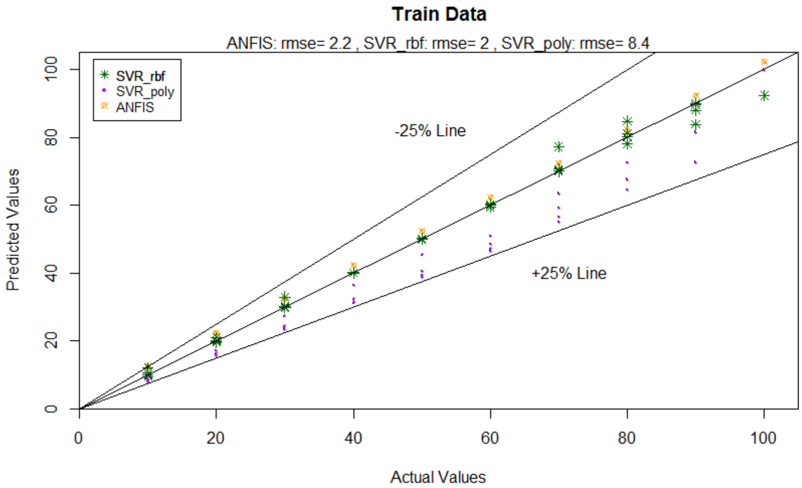


(b)

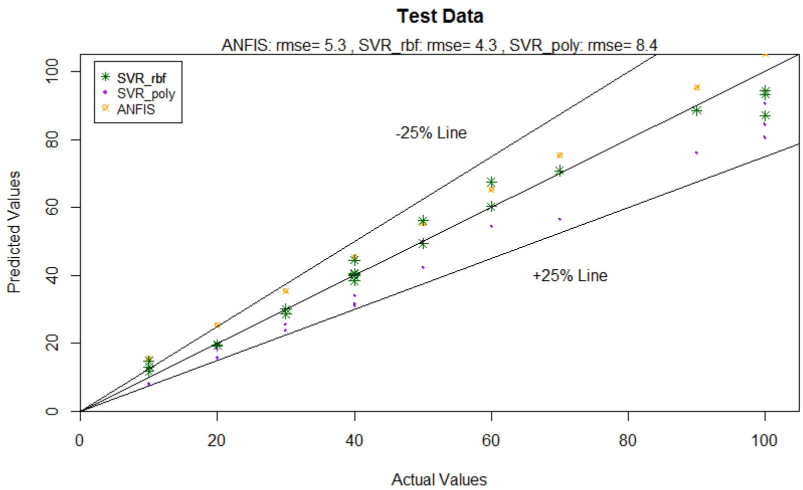
Fig. 4. Performance of SVR_rbf, SVR_poly and ANFIS on the SVR_2 case in (a) training phase and in (b) testing phase.

The initial data was used to establish the polynomial and RBF kernel SVR. The data was predicted using RBF and polynomial. The results of R2 and RMSE of the SVR_1, SVR_2 and SVR_3 models are presented in Figs. 3, 4 and 5 in terms of training and testing. The SVR_rbf and SVR_poly models in the SVR_1 had very small RMSE (ranging from 0.59 to 5.1) during training and RMSE (ranging from 3.5 to 5.1). The models showed consistently good correlation throughout training and testing.

Figures 3(a), 4(a) and 5(a) illustrate the results with the performance indices between predicted and observed data in the training phase, while Figs. 3(b), 4(b) and 5(b) indicate the results for the testing phase, respectively. Although the performance of SVR_rbf and SVR_poly on the SVR_1 case in the testing phase is not on a par with other sides, due to the



(a)



(b)

Fig. 5. Performance of SVR_rbf, SVR_poly and ANFIS on the SVR_3 case in (a) training phase and in (b) testing phase.

small number of samples (training data), the optimal kernel function type of SVR is RBF in the SVR_1 case dataset. It can be seen that SVR_rbf performed well in predicting wind speed. Comparing SVR_rbf results with SVR_ poly reveals that SVR_rbf outperforms the RBF model in terms of prediction accuracy and ANFIS as well.

8. Performances of the Models

The root mean squared error (RMSE) and coefficient of determination (R^2) were used to evaluate the differences between the expected and actual values for both SVRs with

Table 3
Performances of the analyzed models.

Experiments	Method	Training		Testing	
		Error (RMSE)	Coefficient of determination (R^2)	Error (RMSE)	Coefficient of determination (R^2)
SVR_1	SVR_rbf	0.59	0.422	3.5	0.441
	SVR_poly	5.1	0.75	5.1	0.758
SVR_2	SVR_rbf	1.2	0.696	1.9	0.721
	SVR_poly	5.2	0.687	5.2	0.698
SVR_3	SVR_rbf	2	0.982	4.3	1.001
	SVR_poly	8.4	0.802	8.4	0.836
ANFIS_1		0.94	0.612	3.8	0.989
ANFIS_2		2.2	0.986	2.6	0.924
ANFIS_3		2.2	0.986	5.3	0.658

ANFIS. Table 3 compares the SVR_rbf, SVR_poly models with the ANFIS. The results in Table 3 indicate that the SVR_rbf has the most significant effect on wind speed estimations. For instance, RMSE $= 0.59$ in the training phase for SVR_rbf in (SVR_1) is less than RMSE $= 5.1$ for SVR_poly in the same situation.

9. Conclusion

In this paper, novel algorithms for wind speed estimation in wind power generation systems were proposed, which is based on the soft computing techniques. The inputs are wind turbine power coefficient, rotational speed and blade pitch angle.

Wind energy is a rapid growing industry, and this growth has led to a large demand for better modeling and prediction of wind turbine output energy. The uncertainties and difficulties in measuring the wind inflow to wind turbines makes the prediction difficult, and more advanced modeling via system identification techniques and a number of advanced prediction approaches should be explored to reduce the cost of wind energy. A systematic approach to achieving the wind speed by means of support vector machine (SVR) strategy and ANFIS methodology was investigated.

This paper presents a support vector regression (SVR) technique for the wind speed estimations. Two SVRs were investigated: radial basis function (SVR_rbf) and polynomial function (SVR_poly). The result showed that the SVR_rbf is better than SVR_poly in prediction of the wind speed. The performance of the SVRs models were compared against the ANFIS results. The SBR-rbg was better than ANFIS in terms of root mean square error and coefficient error. SVR model with three inputs (SVR_2): blade pitch angle, rotor speed and power coefficient has the best prediction results for the wind speed in testing phase.

Acknowledgements. This paper is supported by Project Grant TP35005 “Research and development of new generation wind turbines of high-energy efficiency” (2011–2015) financed by Ministry of Education, Science and Technological Development, Republic of Serbia.

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Vėjo greičio įvertinimas nenaudojant jutiklių pagal lanksčiosios kompiuterikos metodologijas: lyginamoji analizė

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Šiame straipsnyje aptariami keli nauji vėjo greičio įvertinimo būdai, pagrįsti lanksčiosios kompiuterikos metodais. Įvertinimų įvesties duomenys yra vėjo turbinos galios koeficientas, sukimosi greitis ir mentės pasvirimo kampas. Siekiant įvertinti vėjo greitį naudojamas atraminių vektorių regresijos metodas, o jame branduolio funkcijos – polinominė ir radialinė bazinės funkcijos. Vietoj stebimos mokymo paklaidos minimizavimo, minimizuojamos bendros paklaidos ribos, taip gaunamas apibendrintas įvertinimas. Gauti rezultatai palyginami su adaptyvaus neuro-fuzzy (ANFIS) metodo rezultatais.