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Research Article

Torque Prediction Based Performance Analysis of Small-Scale Wind Turbines Using Data-Driven Modelling Methods

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Abstract

In this study, the rotor torque of wind turbines has been predicted using machine learning approach based on real time data which have been collected for the designed small scale Savonius and four leaves rotors. The tip speed ratio (TSR) has been selected as the main input parameter in machine learning modelling technique which are linear regression (LR), support vector machine (SVM) regression and Gaussian process (GP) regression. The hyperparameter of these models have been defined by grid search method. RMSE, determination coefficient, MSE and MAE have been used to evaluate the predictive performance of the models to experimental data. The rotor torque modelling results show the efficiency of wind turbines can be maximized with high estimation accuracy of models. On the other hand, it has been also observed that torque of the Savonius type wind turbine is higher than the four leaves turbine

Keywords: Savonius turbine, Four Leaves Turbine, Modelling, Machine Learning Techniques

Veriye Dayalı Modelleme Yöntemleri Kullanarak Küçük Ölçekli Rüzgar Türbinlerinin Tork Tahmin Tabanlı Performans Analizi

Öz

Bu çalışmada, rüzgar türbinlerinin rotor torku, tasarlanan küçük ölçekli Savonius ve dört yaprak rotor için toplanan gerçek zamanlı verilere dayanan makine öğrenme yaklaşımı kullanılarak tahmin edilmiştir. Uç hız oranı (TSR), makine öğrenimi modelleme tekniğinde doğrusal regresyon (LR), destek vektör makinesi (SVM) regresyonu ve Gauss işlemi (GP) regresyon yöntemlerinde ana giriş parametresi olarak seçilmiştir. Bu modellerin hiperparametreleri ızgara arama yöntemi ile tanımlanmıştır. RMSE, R^2, MSE ve MAE, modellerin deneysel verilere tahimin performansını değerlendirmek için kullanılmıştır. Rotor tork modelleme sonuçları, rüzgar türbinlerinin verimliliğinin modellerin yüksek tahmin doğruluğu ile en üst düzeye çıkarılabileceğini göstermiştir. Öte yandan, Savonius tipi rüzgar türbininin torkunun dört yapraklı türbinden daha yüksek olduğu gözlemlenmiştir.

Anahtar Kelimeler: Savonius türbini, Dört Yapraklı Türbin, Modelleme, Makine Öğrenme Teknikleri

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1. Introduction

Today, the interest in alternative energy sources, also known as renewable and inexhaustible sources of energy is increasing day by day due to the stringency of environmental regulations, decreasing fossil fuel reserves. One of the most preferred among these sources is wind energy to reduce the impact of greenhouse gas emission on climate change. It is estimated that there is about 10 million MW wind energy in the World (GWEC (Global Wind Energy Council), 2017).

The wind energy occurs at the high- and low-pressure zone from constantly changing airflow. Therefore, the amount of wind power source may differ considerably between geographic regions of the world. The motion energy of wind caused by the pressure difference converts into mechanical energy through turbines.

Wind turbines are classified into two categories, vertical and horizontal axis wind turbines. Horizontal axis wind turbines are parallel to the ground while vertical axis turbines are perpendicular to the ground. Especially, horizontal axis turbines are more advantageous and their efficiency is high than vertical ones when the wind direction and speed are very variable (Gasch & Twele, 2012). The vertical axis turbines are preferred in low speed winds. The turbines are produced in different structures such as Savonius, Darriues turbines to improve their performance (Wenehenubun, Saputra, & Sutanto, 2015).

Savonius type turbines, also known as S-rotor, consist of three or four blades. These turbines are more suitable for applications requiring high torque and low speed due to turbulence on the blade of the turbine (Gasch & Twele, 2012). There are many studies on the electricity production by using the type of Savonius wind turbine. In one of the studies, Hayashi et al. (2005) investigated the performance of three-bladed Savonius turbine with 120 degrees difference (Hayashi, Li, & Hara, 2005). In another study, researchers examined the angular distance effect of the blades (Al-Shamisi, Assi, & Hejase, 2013). Results of two and three bladed turbines study were also compared in low speed wind. McWilliam et al. (2008) developed the model of the Savonius turbine to investigate the vortex by using particle image velocimetry (PIV) in the wind tunnel (McWilliam & Johnson, 2008).

In many research, the aerodynamic characteristics of both vertical and horizontal axis wind turbines were investigated by considering many design parameters (Fujisawa & Gotoh, 1994; Kawamura T., Hayashi T., & Miyashita, 2001). Apart from these studies, other studies include modeling and simulation of wind turbine on rotor performance by predicting power and torque characteristics, which focus on the use of heuristically methods, including artificial neural network (ANN) (Kalogirou, 2000; Sargolzaei & Kianifar, 2009).

The data-driven modelling and prediction methods based on machine learning (ML) have emerged as a tool for catching the complex dynamic systems (Hafner & Isermann, 2003; Shah, Zhao, Delvescovo, & Ge, 2019). The designed ML model for the system can be considered as an input-output function learning directly from attributes of experimental data (Russell & Norvig, 2016)

The purpose of this study is implementing different ML algorithms and comparing their rotor torque prediction performance of wind turbines such as Savonius and vertical turbines. In the present study, the four leaves and micro Savonius type of wind turbine model experimental setup have been established and the prediction models are designed for rotor torque prediction in according to tip speed ratio and generated electrical voltage using dc generator. Then, the obtained models have been verified with these data. Consequently, the obtained results show that Savonius type wind turbine rotor torque efficiency outperforms other four leaves turbine model.

2. Material and Methods

The Test Rotors and Experimental Test Setup

The experiments used a model of Savonius and four leaves rotor micro models as shown in Fig. 1.

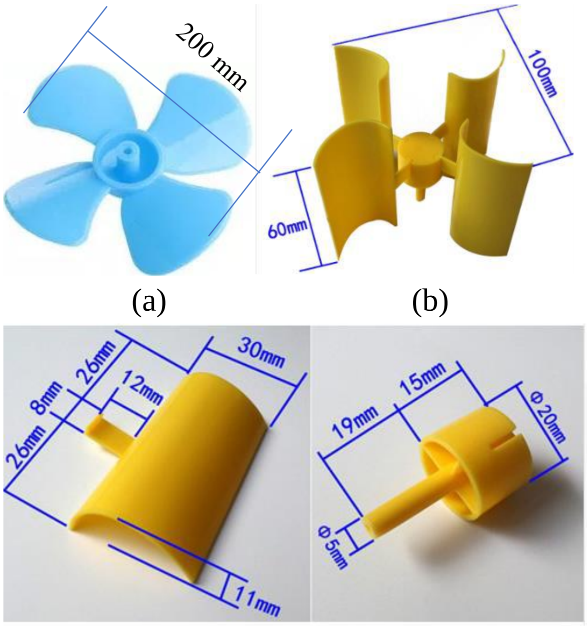

Fig. 1. Design of turbine models (a) four leaves rotor (b) Savonius rotor

Fig. 2 shows the DC generator equipment turbine-generator experimental setup.

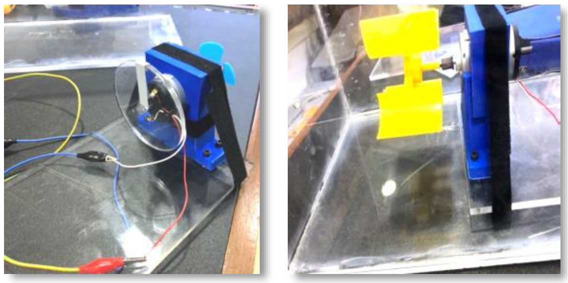

Fig. 2. The turbine rotor-DC generator experimental setup

As shown as Fig. 2, Mitsumi DC M36N-2 motor has been used in the experiments. Besides, the voltage and the speed of wind parameters have simultaneously measured by using Yokogawa TY720 digital multimeter and Benetech GM816 flowmeter, respectively.

The Calculation Parameters of Wind Turbines

The wind turbines operate thanks to the applied pressure on the blade. The wind force is perpendicular to the blade surface and the blade rotates through rotor torque that applied on the shaft. To define power or torque of the turbine, wind power and efficiency of the wind turbine parameters must be calculated. Firstly, the swept area of the turbine is calculated, using the following expression

$$A = \pi L^2 \; for\ horizontal\ wind\ turbine$$
$$A = DH \; for\ vertical\ wind\ turbine \qquad (1)$$

Here, L is the length of blade. D and H denote diameter and height of vertical axis wind turbine, respectively. Then, wind power is expressed as follows:

$$P_{wind} = \frac{1}{2}\rho\vartheta^3 A \qquad (2)$$

where, ρ is air density and $\rho = 1.225\frac{kg}{m^3}$. ϑ present wind speed.

The total efficiency of the turbine as follows.

$$\zeta = (1 - k_{\mathrm{m}})\,(1 - k_{\mathrm{e}})\big(1 - k_{e,t}\big)\,C_{\mathrm{p}} \quad (3)$$

In the Eq. (3), k_{m}, k_{e}, $k_{e,t}$parameters denote mechanical, electrical, transmission to grid losses, respectively. C_{p} is turbine efficiency and the parameter being lower than Betz limit. Finally, the turbine power and rotor torque are calculated below.

$$P_{out} = \zeta\, P_{wind}$$
$$\tau_{rotor} = \left({}^{P_{out}}/_{N_{turbine}}\right)\left({}^{30}/_{\pi}\right) \quad (4)$$

In this study, the main input parameter of the designed models is tip speed ratio (γ). The parameter can be defined using the following equation.

$$\gamma = \frac{u}{\vartheta} = \frac{\omega D}{2\vartheta} \quad (5)$$

where, D is diameter of turbine rotor and ω is the angular speed of the rotor.

The Machine Learning (ML) Methodologies

The first step of the ML procedure is pre-processing of the designed turbine rotor. Firstly, different number of datasets was acquired for different wind speed conditions. Then, each dataset such as the speed of wind, tip speed ratio and the output of the DC generator parameters were scaled by normalization formulation.

In the second stage of the preprocessing, data of all models were carried out by using k-fold cross-validation to ensure performance predictive performance and stability of the designed ML models with 5 folds. For this purpose, data set has been splited into 5% for training and 95% for testing. Finally, 95% part of the dataset is separated.

ML regression models are very sensitive to hyperparameter changes of the models. After the model is chosen to define relationship between input and output of the turbine rotor system, the parameter the models is required to set to obtain optimally prediction performance. There are different types and numbers of parameter for each ML models. Different combinations of hyperparameter are defined by using an optimization technique that minimizes the error between model output and measurement results for a considered model type. Therefore, obtaining successful results from the designed ML models depends on the correct determination of hyperparameters. In this study, the grid search algorithm has been used for determination hyperparameters of ML models.

In this paper, different ML models were created by using Linear Regression (LR), Support Vector Machines Regression (SVR) and Gaussian Process Regression (GPR) algorithm to predict the rotor torque of designed wind turbines.

The first algorithm is LR which aims to express relationship between the input and output parameters of turbines and expressed mathematically as follows.

$$Y_{torque} = a + bX_{tip\ speed\ ratio,generated\ voltage} \quad (6)$$

In Eq. (6), b defines slope of the line that intercepted by a parameter.

The second ML algorithm is SVR which one of the supervised learning techniques.

The purpose of SVR model is to estimate a function that the output data is as close as possible to measurement result with the input parameters. This estimated function is expressed in the following form.

$$\psi(x) = \omega \cdot \varphi(x) + b \tag{5}$$

In the Eq. (5), b is bias. In the SVM model, the kernel function (linear) that calculates the data transformations is employed $\kappa(x,\hat{x}) = \varphi(x) \cdot \varphi(\hat{x})$. The used kernel functions in SVM are linear, polynomial, quadratic and gaussian.

The last ML modelling method which was used in the study, is GPR that is defined for given a training dataset that contains inputs and output data. y indicates the Gaussian distribution of the input x variables expressed as follows

$$\mu(x) = \mathbb{E}[y(x)]$$

$$GD(y) = \frac{1}{\sigma\sqrt{2\pi}} e^{(y-\mu)^2 / 2\sigma^2} \tag{7}$$

Here, σ and μ demonstrate standard deviation and mean of distribution, respectively. GPR requires positive defined covariance matrix and shown as $\kappa(x,\hat{x})$. The prediction of the output variable is given by

$$\bar{y}^* = \mu(x^*) + \kappa(x^*,x)\kappa_y^{-1}(y-\mu(x)) \tag{8}$$

$$g(x)^T\beta + f(x) \tag{9}$$

Evaluation of prediction performance metrics

The error prediction performance of the LR, SVR and GPR models were evaluated using four indicators, including mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), and determination coefficient (R2). The performance evaluation metrics in model output variables are given as follows.

$$MAE(y_{torque}, \hat{y}_{torque}) = \frac{\sum_{k=1}^{N} \left| y_{k\,torque} - \hat{y}_{k\,torque} \right|}{N}$$

$$MSE(y_{torque}, \hat{y}_{torque}) = \frac{1}{N}\sum_{k=1}^{N}\left(y_{k\,torque} - \hat{y}_{k\,torque}\right)^2$$

$$RMSE(y_{torque}, \hat{y}_{torque}) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(y_{k\,torque} - \hat{y}_{k\,torque}\right)^2}$$

$$R^2(y_{torque}, \hat{y}_{torque}) = 1 - \left(\frac{\sum_{k=1}^{N}\left(y_{k\,torque} - \hat{y}_{k\,torque}\right)^2}{\sum_{k=1}^{N}\left(y_{k\,torque} - \bar{y}_{torque}\right)^2}\right) \tag{6}$$

Here, y_{torque}, $\hat{y}_{torque}$ and $\bar{y}_{torque}$ denote actual, estimated and average value of turbine rotor torque, respectively.

3. Result

In this subsection of the study, the turbine rotor torque and tip speed ratio were calculated by using Eq.1-5. The relationships between wind speeds and tip speed ratio for type of turbine rotor are shown in Fig. 2 and Fig. 3.

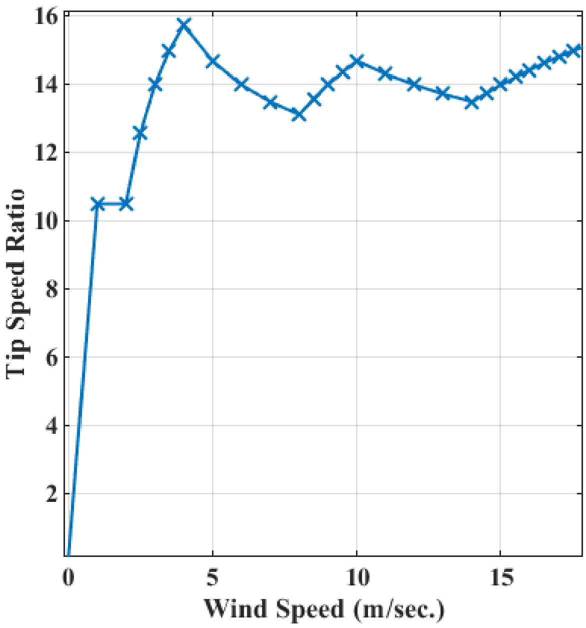

Fig. 3. Tip speed ratio related with wind speed (m/sec.) of Savonius Turbine

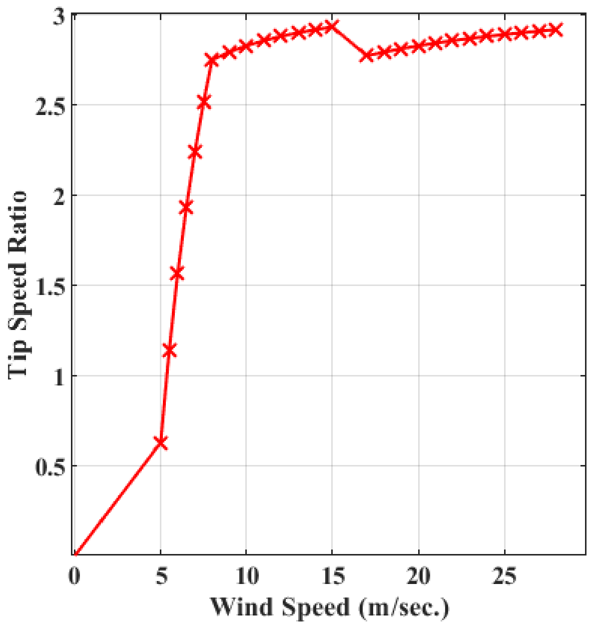

Fig. 4. Tip speed ratio related with wind speed (m/sec.) of turbine with four leaves rotor

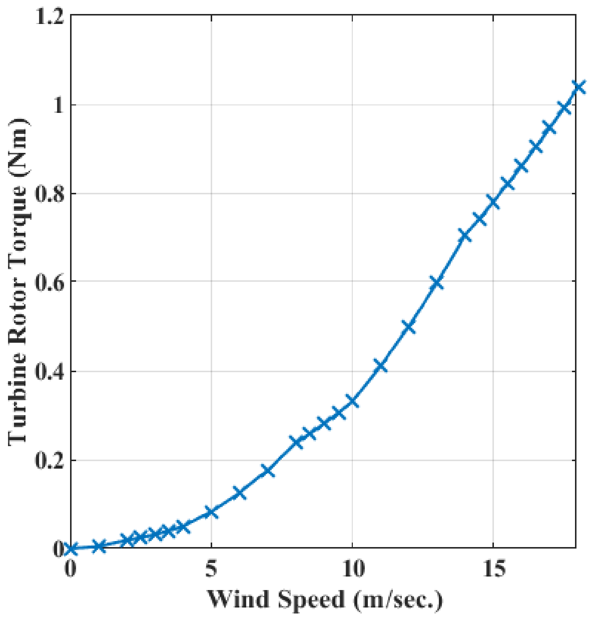

Fig. 5. Torque of wind Savonius turbine rotor for different wind speeds (m/sec.)

As shown in Fig. 3 and Fig. 4., Savonius wind turbine rotor have maximum tip speed ratio at lower wind speed (<5 m/sec.) and more stable than turbine with four leaves rotor at about wind speed of 7 m/s. The tip speed value must be small in reaching optimal rotational speed levels of turbines. Besides, the torque of the turbine rotor is related with the performance of the wind turbine. For this purpose, the rotor torque is plotted depending on the wind speed as shown in Fig. 5 and Fig. 6.

The differences between the rotor torques of the of Savonius and four leaves wind turbine are highlighted in Fig. 5 and 6. Because of the blade structure of Savonius turbine, it has higher rotational torque than other wind rotor model.

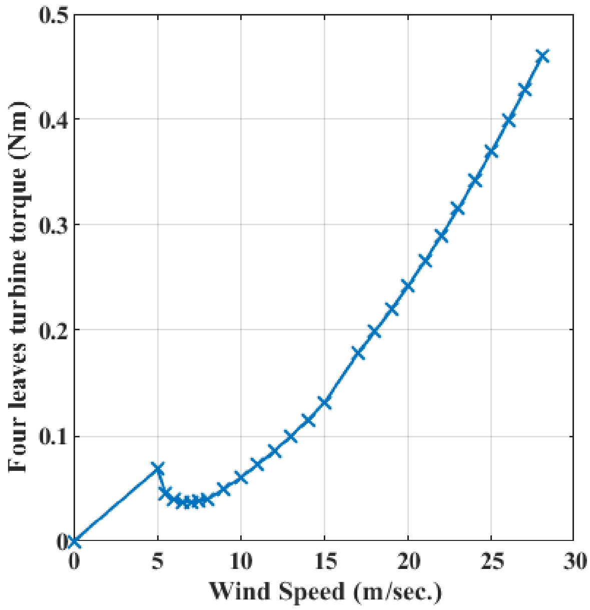

Fig.6. Torque of four leaves rotor for different wind speeds (m/sec.)

In the research, the rotor torque and tip speed ratio of turbines have been modelled as a function of wind speed and generated voltage by using different ML algorithms. Firstly, in the present article, the first modelling method is applied as LR.

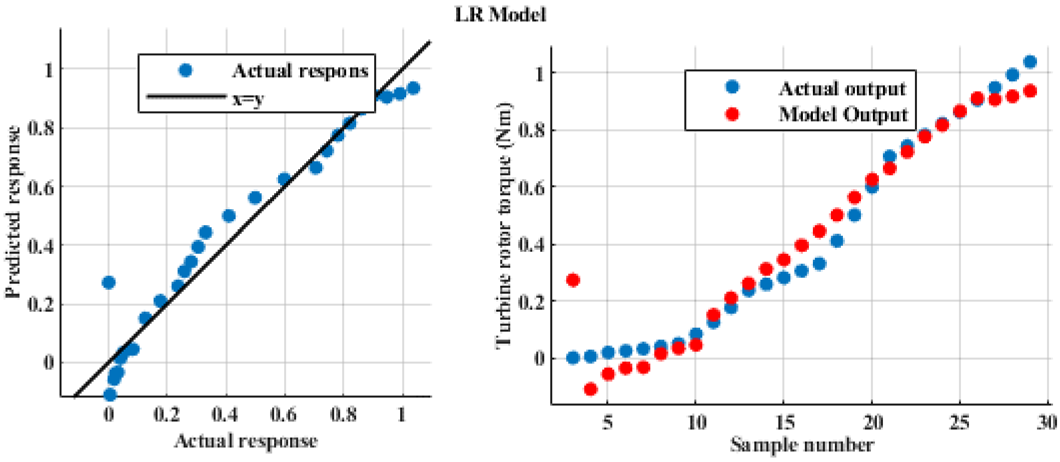

Fig. 7. Comparison between values of measurement and the LR model for Savonius rotors

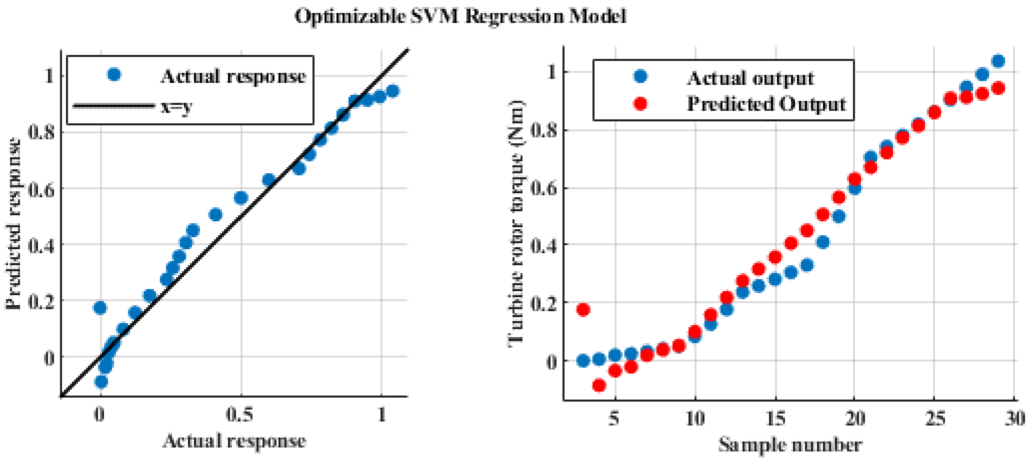

Fig. 8. Comparison between values of measurement and the SVR model for Savonius rotors

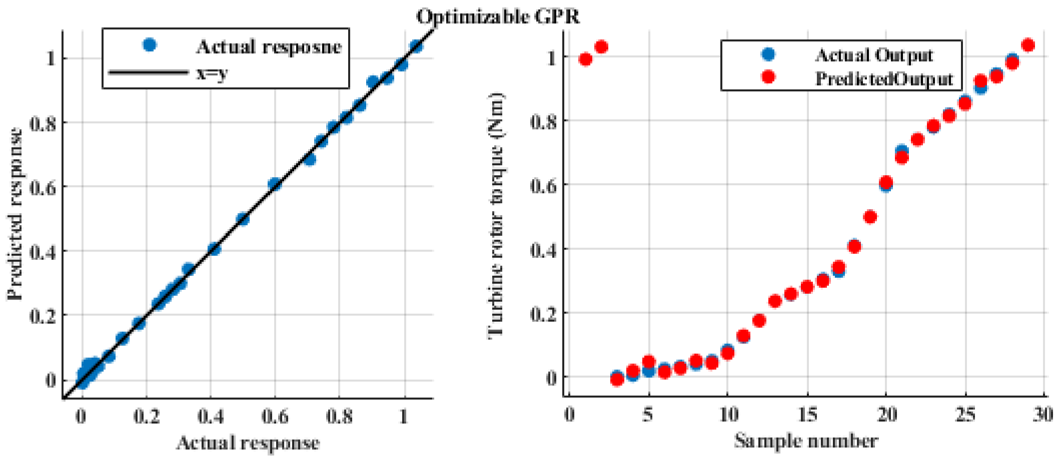

Fig. 9. Comparison between values of measurement and the GPR model for Savonius rotors

Fig. 7-9 illustrate the performance of designed LR, SVR and GPR models for Savonius turbine rotor. The blue circles in these figures show measurement torque data and the model outputs indicate by red colour in the figure, respectively. The success rate of LR is decreasing of the MSE, RMSE and MAE. The other method is determination coefficient (R) which its value is required to be as possible close to 1. The coefficient of determination (R2) for Savonius turbine rotor torque predicted by the LR, SVR, and GPR models are 0.95, 0.97 and 0.99, respectively. The RMSE is determined to be 0.078423, 0.064852, and 0.01551 for the models, given as Table 1, respectively. The plots generated by GPR model pass through every training torque data point.

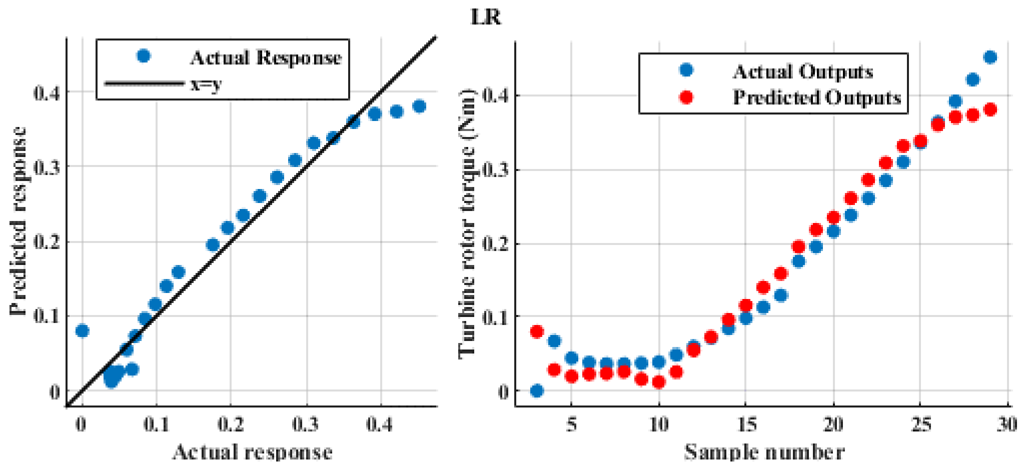

Fig. 10. Comparison between values of measurement and LR model for turbine rotor with four leaves

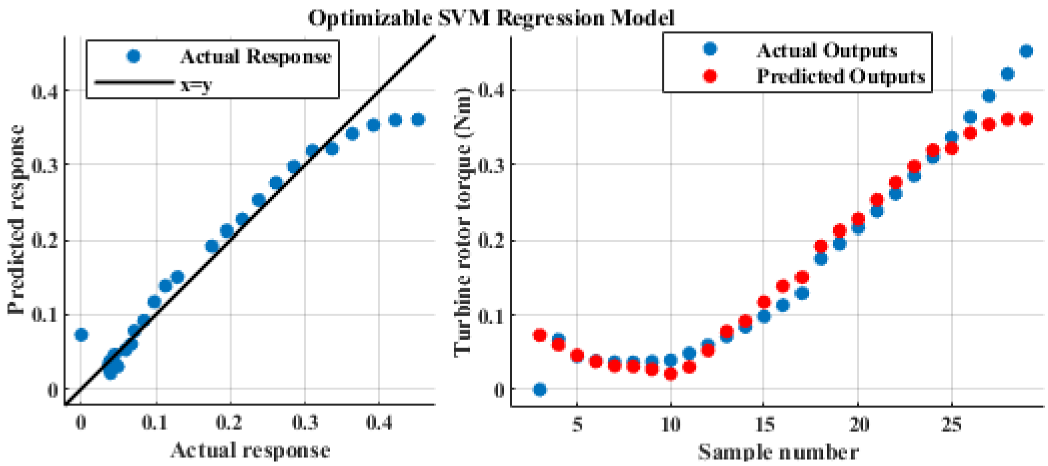

Fig. 11. Comparison between values of measurement and SVR model for turbine rotor with four leaves

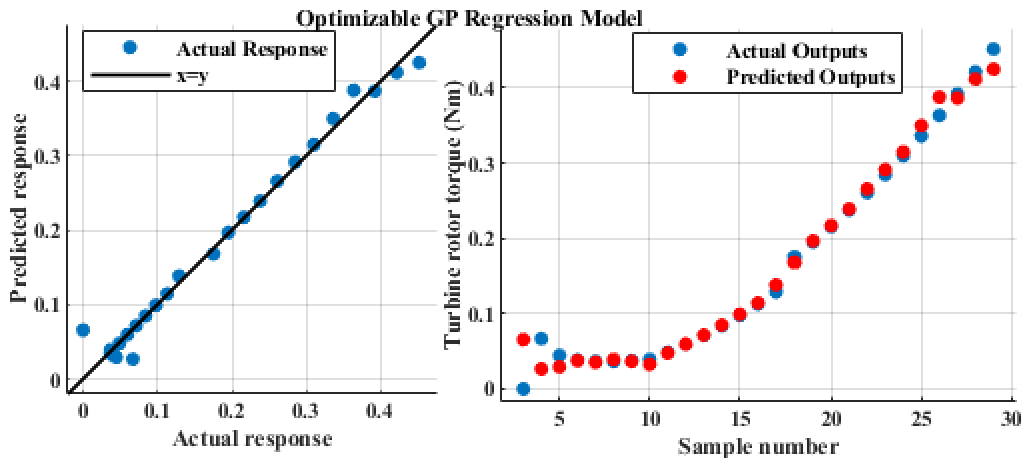

Fig. 12. Comparison between values of measurement and GPR model for turbine rotor with four leaves

As shown in Fig. 10- 12, the comparison between the actual and model output data for LR, SVR and GPR models for turbine with four leaves. It can be seen that the predicted values for both model graphs, for the minimum RMSE from data, are in very good agreement with measurement data.

The hyperparameter effects of designed SVR and GPR models for both turbine rotor models have been investigated in this study. To express the effect of hyper-parameters on prediction performance of the SVR model, the grid search algorithm has been employed to tune the optimal parameter. Three optimizable hyperparameters have been used for the SVR. The gaussian, linear, quadratic has been varied as kernel function. The hyperparameter estimation of GPR affect to significantly model predictive performance. In this research, squared exponential, exponential and rational quadratic were used as kernel function for the mean and covariance functions have been specified by hyperparameters.

Tablo 1. Error analysis of the designed ML models

Savonius rotor	**ML models**	**RMSE**	**R^2**	**MSE**	**MAE**
	LR	0.078423	0.95	0.0061502	0.05738
	SVR	0.064852	0.97	0.0042058	0.049417
	GPR	**0.01551**	**0.99**	**0.000111**	**0.0078**
The four leaves turbine rotor	LR	0.02987	0.95	0.0008921	0.024
	SVR	0.029351	0.96	0.000086	0.02037
	GPR	**0.017277**	**0.98**	**0.0000298**	**0.0094417**

4. Conclusion

In this study, machine learning modelling approach has been presented to predict the rotor torque in a Savonius and four leaves wind turbine according to tip speed ratio. The performance analysis of the small-scale wind turbine has been analyzed by using designed models. The obtained results show that the prediction accuracy from GP in machine learning method is high and compatible with real-time data. The machine learning algorithms capture wind turbine dynamics. The results of this research present that GP regression method is the best method among the four data-driven methods for prediction of torque output variables based on RMSE, R2, MSE and MAE evaluation criteria. In addition, the result of this modeling and experimental study shows that Savonius has high torque compared with four leaves wind rotor. These findings may help us to understand that Savonius wind turbine has good performance in terms of four leaves turbine at lower tip speed ratio.

5. Acknowledgement

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