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Short-term Solar Power Forecasting using SVR on Hybrid PV Power Plant in Indonesia

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Abstract. Considering the environmental issues, the use of renewable energy sources is a far more sustainable solution to meeting the energy demand than fossil fuels. However, the limited availability of renewable energy is a growing problem to be solved. Solar energy has become a popular renewable energy source in several countries such as Indonesia because of their equatorial locations. In this study, limited meteorological measurement has been applied with the aim of forecasting solar power generation for planning photovoltaic (PV) power plants, especially in rural areas, which have limited access to fossil energy. We used limited measurements such as temperature, humidity, and solar radiation. The use of support vector regression (SVR) was applied to improve denoising capabilities and simplify computation. SVR has been evaluated using statistical metrics such as mean absolute percentage error (MAPE), relative root means square error (NRMSE), and coefficient of determination (R^2). The results showed the MAPE value obtained 18.56% from the RBF_SVR. NRMSE value performed excellently with 8.02% from the SW-SVR method. R2 also indicated good forecasting with 0.99. The results showed that promising short-term solar power generation forecasting can be applied to estimate the availability of solar power, plan for an extension, and assess the performance of hybrid power plants in Indonesia.

1. Introduction

Renewable energy is an important issue that is addressed in several international treaties such as the Kyoto Protocol and the Paris Agreement. Several points have been raised, such as the need for reducing global temperatures, increasing renewable energy use, reduction of greenhouse gas emissions, and financial support to implement these programs. The use of fossil fuels has increased the amount of harmful gases being released into the air; by increasing the use of renewable energy, this can be reduced. Solar energy is one of the most effective forms of renewable energy, with advantages such as low maintenance, high efficiency, and abundant natural availability. In addition, the power potential of solar radiation in Indonesia is nearly 207.9 MW, and in the equatorial area, the availability of sunlight is almost constant throughout each year.

Solar power generation data is important in order to estimate and evaluate the performance of solar energy resources. However, there are several challenges faced such as limited measurement of meteorological data and long installation times. Artificial intelligence predictions can be used to derive solar power generation data; there are several artificial intelligence methods that have successfully predicted solar power, one of which is SVR. SVR was chosen because this method has been widely used for classification and regression analysis. Meteorological data such as temperature, humidity, duration of solar radiation, and wind speed are used as input. Zeng and Qiao [1] proposed a least-square (LS) support vector machine (SVM)-based model for short-term solar power prediction (SPP) in the USA from atmospheric transmissivity, sky cover, relative humidity, and wind speed data. This study aims to predict global solar power generation using SVR with meteorological data.

Yanting Li et al [2] has applied the regression object based on the complexity of variables that affect photovoltaic (PV) systems, such as weather systems and electrical installations in systems; regression with several input variables is used to predict solar energy. Some of the variables involved are related to the predictors. S. Kanwal et al [3] predicted the availability of power generation such that the generated power would be dispatched to the area requiring it. Energy can be stabilized by coordinating between the independent power generated at the plant and the main power generated by the system, such as the utility grid. M.Z. Hassan et al [4] compared multiple regression based on SVR methods such as linear SVR, SVR-RBF-Kernel with linear regression to analyze the solar radiation prediction and yield feasible results for short-term solar power prediction.

In this study, we used the physical measurements of the meteorological station as explanatory variables. The measurements were taken by the weather station system of the hybrid power plant in Baron Technopark, Yogyakarta, Indonesia. Support vector regression (SVR) was assessed by limited meteorological data measurement. The intermittent nature of solar radiation is a common problem in Indonesia; this forecasting method attempts to solve the heavy cloud and clear sky conditions. Implementation in rural areas, which have limited electrical connectivity, caused us to explore the possibility of integrating the forecasting method with the utility power management system; the model will be applied to open data for public services. Additionally, the purpose of this research is also to plan the extension area of the PV power plant and assess the quality of the system.

2 Methodology

2.1. *Data Analysis*

We proposed a method to process the training and testing data, monitoring data of the hybrid power plant in Baron Technopark. The system consists of a 5 kW wind energy generator, 10 kW wind energy generator, 36 kW photo-voltaic plant, 20 kW diesel engine generator, and a 20 kW lead acid battery system. The system monitoring was also included in the plant. From the monitoring data, it obtained the physical

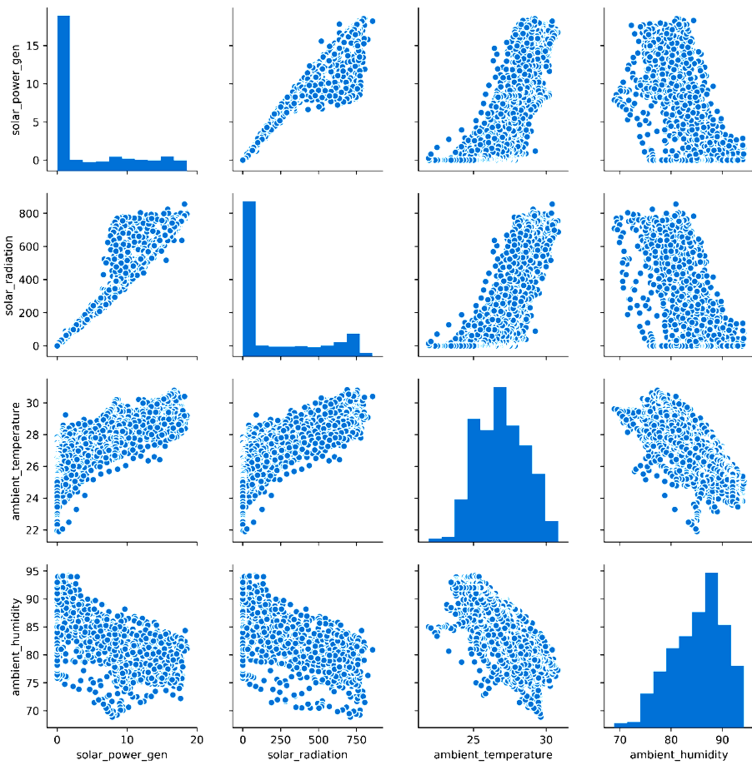

Fig 1. Scatter plot of explanatory variable and response variable for solar power prediction

values from sensors on each power generator. Measured data for a 1 month period (June 2017) was collected from the plant, with an average of 10–11 h of bright sunlight per day. The dataset consisted of ambient temperature, humidity, and wind speed, with a total of 30 days of summer data which is divided into 27 days of training data, 3 days of validation data, and 1 day of testing data.

A 15-minute resolution time was applied in the system to prevent time shifting and unreasonable data in this period [5]. It was provided after averaging the data from each variable. Fig 1. has indicated a correlation between solar power and other predictors. The solar radiation, ambient temperature and ambient humidity are the parameters which show close relationships to the solar power, with solar radiation being the solar variable showing the closest relationship. From the scatter, the plot looks at the linear relationship between solar power and solar radiation, ambient temperature, and humidity environment. The three explanatory variables showed a significant linear correlation with solar power. From the graph presented, there are several data outliers between the variables. The outliers can be attributed to several factors such as errors in sensor readings, lost data, and loss of power in the sensor. Data distribution on the histogram also shows that solar power has a centralized distribution of data at 0 and 19 kW. This indicates that there is no solar radiation at night, while the 19 kW value is the value of solar radiation in the maximum radiation time period from 10.00 to 14.00 hours. The solar power generation histogram also describes data distribution in solar power generation. This data illustrates the 75% data distribution in the range of 0–10 kW. Meanwhile, 25% of the data is in the >10 kW range. The median training data is at 5 kW. There are no data outliers in the dataset. The matrix correlation is shown in Fig 2. The correlation matrix graph

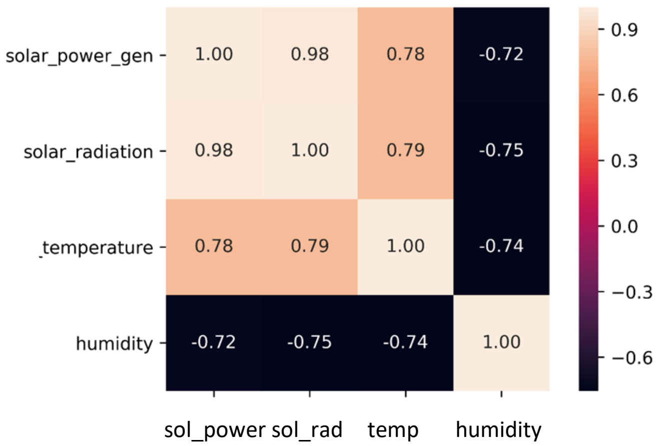

Fig 2. Matrix correlation between variables

describes the correlation between parameters with a square matrix using Pearson's coefficient relation, which connects the explanatory variables and the response variable in the range of -1 to 1. Solar radiation shows a significant correlation to solar power generation, with an index of 0.98. Other significant variables are temperature and humidity, with correlation values of 0.78 and -0.72. This graph shows that explanatory variables and response variables are closely related to the production of accurate predictive values.

2.2. *Support Vector Regression*

SVR finds a function of the predicted value and actual value. Then, the function with the highest deviation from the target value is identified. Making the line was regarded as a hyperplane considering the linearity and separation between the actual and predicted values. The graph did not take errors into account as long as they were less than the error boundary on the hyperplane. The fundamental working principle of SVR is to perform data mapping in certain spaces through non-linear mapping and perform direct calculation in the peculiarity space. On the off-chance that a method for registering the internal item in a feature space is accessible specifically as an issue to the first includes focuses, it is conceivable to construct a non-direct learning machine, which is known as an issue processing technique of a kernel function, denoted by K. The flexibility of SVR is attributed to the kernel that represents the information in a higher-dimensional peculiarity space. A linear solution in the feature space corresponds to a non-linear solution in the original input space.

There are methods that employ non-linear kernels to regression problems and correspondingly apply SVR. One such kernel function is the radial basis function (RBF). The main advantage of the RBF is that it is computationally more efficient than the ordinary SVR method because the RBF needs only a solution of linear equations rather than the computationally demanding quadratic programming requirement in standard SVR. The RBF is a more compressed, supported kernel than other kernel functions. In this study, the parameter σ is adapted for the RBF, which is defined as

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

Where $K(x, y)$ is kernel function, and x and y are vectors of features computed from training or test samples [6]. In this study, there are several SVR methods has been applied for the dataset to predict the solar power generation. The following are the equations of some these SVR methods:

Linear SVR = $K(x, y) = x \times y$ (2)

Polynomial SVR = $K(x, y) = ((x \times y) + c)^d$ (3)

RBF SVR = $K(x, y) = \exp(-\gamma\left||x - y|\right|^2)$ (4)

Where x and y are vectors of features computed from training or test samples, and c is a constant intended to balance influence of higher-order versus lower-order terms in the polynomial. γ and σ are the kernel function parameters of the RBF kernel [7].

2.3. *Sliding Window-based Support Vector Regression*

The sliding window-based support vector regression (SW-SVR) was used to effectively predict solar radiation [8]. The SW-SVR resolves the computational complexity of the biased data, which is a result of errors, noise, and incomplete datapoints. As it is based on SVR, the above-mentioned regression model effectively handles the multidimensionality problem of the dataset. The model finds a function of the predicted value and actual value. Subsequently, the function with the largest deviation from the desired value is considered. After creating training data based on the matrix correlation. SW-SVR extracts effective training data depends on the movement *r* meaning the change of a specialized object during prediction horizons. Movements of training data can be calculated by referring to the time when each training data is observed. The estimated movement r_t is given as follows:

$$r_t = \left||G_t - G'_t|\right| \approx \frac{\sum_{i=1}^{N} w_i \left||x_i - x'_i|\right|}{\sum_{i=1}^{N} w_i} \textit{where } w_i = \frac{1}{||G_t - x_i||^p} \tag{5}$$

N is the number of training data, w is weight vector, and p is a weighted parameter. Subsequently, we obtained the extracted training data, represented by S_t. In the equation below, x_i is the explanatory variable, and y_i is response variable.

$$S_t = \{(x_i, y_i) | ||G_t - x_i|| < ||G_t - G'_t||\} \tag{6}$$

The number of weak learners is adjusted, and the weight parameters were determined from relation between the dataset as specialized data. Thereafter, the fit kernel trick and partial least square method were utilized to resolve the multidimensionality problem of the dataset. The deviations in the predicted values were also calculated by extracting the deviations in the specialized data, as shown in the equation below. The deviations occurred when the training data was obtained.

$$H(P) = \frac{\sum_{t=1}^{N} w_i H_t(P)}{\sum_{t=1}^{N} w_t} where\ w_t = \frac{1}{||G_t - P||^q} \tag{7}$$

Here, G is specialized data before prediction, and G' is specialized data after prediction. $H(P)$ is a hypothesis of each model, and q is a weighted parameter. Despite characteristic variation with time in the test data, SW-SVR always gives priority to specialized models that are more suitable for predicting test data. Owing to the results being comparable, we built hypothesis as trained by linear SVR and thereafter applied the other SVR method for comparison. Finally, the predicted values were obtained.

2.4. *Evaluation*

SVR methods are commonly evaluated using statistical metrics such as the mean absolute percentage error (MAPE) and relative root mean square error (NRMSE) [9]. Additionally, the coefficient of determination, R^2, is also utilized for evaluation by some researchers. All the above-mentioned evaluation methods are used to derive the correlation between the output and input. Explanatory data has some dataset which multidimensional data. It predicted response variable. R^2 is calculated by subtracting the residual sum of squares from 1, and then dividing the result by the total sum of squares.

MAPE is used as the index of prediction error, and the building time is calculated based on the CPU clock time as the index of computational complexity. It is calculated using y_i, $\hat{y}_i$ and n as shown in the equation below.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i} \times 100\% \tag{8}$$

Where y_i and $\hat{y}_i$ are the actual and predicted values, respectively. n is the number of test data. The absolute value obtained by dividing the difference between y_i and $\hat{y}_i$ by the actual value y_i is summed for every predicted point in time and divided by the number of fitted points n. Multiplying the resulting value by 100 gives us the percentage error.

R^2 is often used in statistics for estimating model performances. It provides the fraction of the calculated values that are the closest to the measurement data. While ideal values of all other statistical indicators used in this study are 0, the R^2 values are close to 1, as shown in the equation below:

$$R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}} = \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2} \tag{9}$$

Where SS_{RES} represents the residual sum of squares; SS_{TOT} (proportional to the variance of the data) represents the total sum of squares; y_i is the actual value, and; $\hat{y}_i$ is the predicted value.

NRMSE is the percentage value of the type of statistical metric, i.e., the RMSE.

$$NRMSE = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}}{\frac{1}{N}\sum_{i=1}^{N} y_i} * 100 \tag{10}$$

RMSE, which is also a method of evaluating metrics, gives the standard deviation of residuals or prediction errors. A residual is the difference between the predicted value and actual value. NRMSE is obtained by dividing the RMSE value by the average measurement value, and then multiplying the result by 100. In our study, we used a notebook computer having the following specifications: Intel i5 7200U CPU, 16GB RAM, 500GB HDD, and Intel HD Graphics 620, and the scikit-learn module with Python 2.7 version for running the SW-SVR model, and subsequently, performance evaluation was conducted, and the statistical metrics were obtained [10].

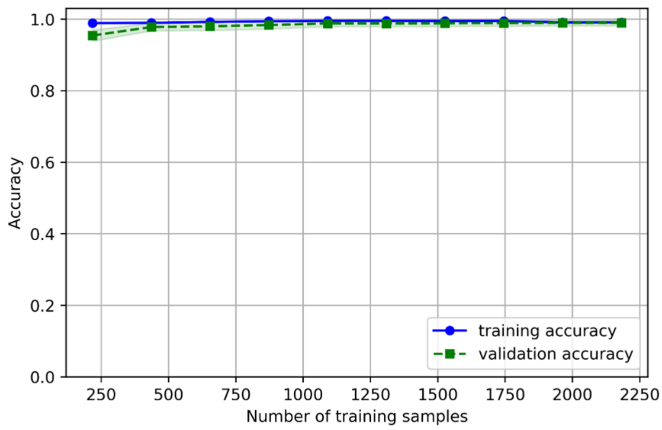

Fig 3. Learning curve of training dataset

3 Results and Discussion

For building the training and testing dataset for solar power prediction, data were recorded over a period of 30 days. We divided the collected data into training and testing datasets for short-term prediction. Before performing hyperparameter tuning, the training dataset was analyzed using the learning curve of the dataset and validation curve of the parameters.

From Fig 3, it can be seen that for the training dataset, the accuracy values for training and validation are in good agreement with one another. The model was verified after analyzing its learning curve. If in the learning curve plot, training accuracy and validation accuracy curves lie close to one another in the exterior of the desired accuracy region, it means underfitting has occurred. On the other hand, if there is a gap between the curves of training accuracy and validation accuracy in the region desired accuracy, it means overfitting has occurred.

From the learning curve plot, it can be seen that although the training accuracy and validation accuracy curves were close to each other, the desired accuracy region was still obtained. The model showed reasonable performance on validation and training accuracies. The gap between the training and validation accuracy curves is insignificant, indicating that sufficient data were acquired for accurate parameter selection. From the Fig. 3 also showed a good spot above 1250 training data. It was found that training dataset with less than 500 datapoints led to underfitting, while, the one with more than 2250 datapoints led to overfitting.

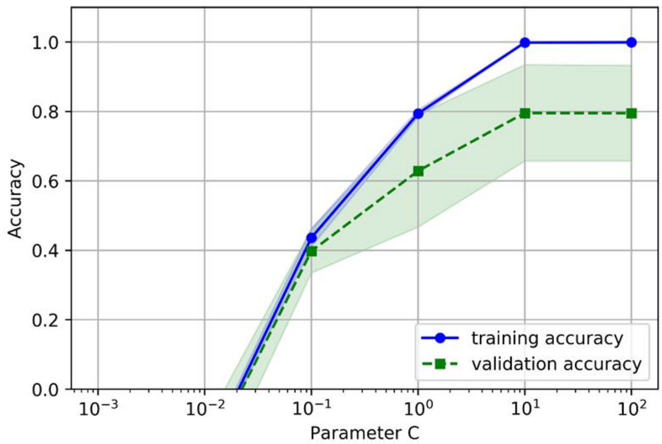

Fig 4. Validation curve for parameter C of the training dataset

The learning curve was also evaluated using stratified k-fold cross-validation. The data were divided to 9 using the cross-validation parameter, proportional of the training and testing data. From the validation curve, shown in Fig. 4, it is observed that for parameter C, a value of 0.1 gives a low accuracy even though training and validation values are nearly identical. Therefore, there is a possibility of an underfitting situation. Meanwhile, if the value of parameter C reaches 0.8 or 80%, then the problem of overfitting may occur. Therefore, the selection of parameter C also needs to be considered during hyperparameter tuning to produce accurate predictions.

The SVR utilized hyperparameter tuning in which dependent parameters or kernel functions, such as Epsilon, C and RBF Gamma were optimized [11]. Effects of appropriate hyperparameter tuning reflects in the form of accurate predictions and results.

Table 1. Comparison results of SW-SVR, linear_SVR, RBF_SVR, and Poly_SVR

Method	NRMSE		R^2		MAPE	
	Validation	Test	Validation	Test	Validation	Test
SW-SVR	9.98	8.02	0.98	0.99	21.26	24.04
linear_SVR	9.57	9.37	0.97	0.97	42.78	74.02
RBF_SVR	10.24	9.42	0.97	0.97	23.70	18.56
Poly_SVR	12.19	17.35	0.96	0.91	19.47	24.16

All the comparison results are listed in Table 1. Based on these results, the predicted and real value distributions were obtained The predicted values were evaluated using NRMSE and MAPE, and the evaluations showed different characteristics. In NRMSE, the data move the squares so that the presence of outliers to be larger if no error distribution outlier would be ideal if at the root squared. Therefore, MAPE can be considered to be more robust as it is less sensitive to outliers, although this assumption cannot be generalized for every dataset.

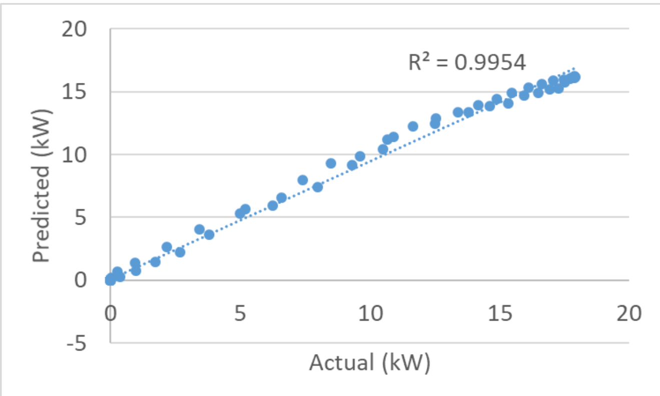

Fig 5. Linear correlation between actual (kW) and predicted (kW)

Short-term prediction at testing period can be done by considering a minimum MAPE value of 18.56%. The interpretation of MAPE (%) values was explained in terms of forecasting by Lin, K-P and Pai, P-F (2016) [12] as mentioned in the following: less than 10% indicates excellent forecasting, 10%–20% indicates good forecasting, 20%–50% indicates fair forecasting, and 50% or more indicates poor forecasting. According to this, MAPE value of RBF-SVR falls under good forecasting. There are several variables that affect the solar power generation, such as electrical system, instrument system, and wiring. NRMSE results are shown in the table for short-term prediction at testing period. Minimum NRMSE value is found to be 8.02%, which is obtained from SW-SVR. The interpretation of NRMSE (%) values was suggested by K. Mohammadi et al (2015) as mentioned in the following: less than 10% indicates excellent forecasting, 10%–20% indicates good forecasting, 20%–30% indicates fair forecasting, and 30% or more indicates poor forecasting. The short-term prediction at testing period for SW-SVR shows an excellent forecasting result as the NRMSE value is less than 10%.

Table 1 shows the short-term prediction of solar power generation for validation period. In the validation period, MAPE scores of SW-SVR, linear_SVR, RBF_SVR, and Poly_SVR are 21.26%, 42.78%, 23.7%, and 19.47%, respectively. The results vary in the range between 19%–40% approximately, that is between good and fair forecasting. A good forecasting is obtained from Poly_SVR and a fair forecasting from linear_SVR. In addition, the model has been evaluated by using coefficient of determination (R^2). R^2 scores of SW-SVR, linear_SVR, RBF_SVR, and Poly_SVR are 0.98, 0.97, 0.97, and 0.96, respectively. Fig 6. and the R^2 scores indicate linearity between predicted and actual values for all methods. The value of SW-SVR was close to 1 despite the weather conditions where dry or summer season data were recorded along with several rainy cloudy days. NRMSE values in validation period for SW-SVR, linear_SVR, RBF_SVR, and Poly_SVR are 9.98%, 9.57%, 10.24%, and 12.19%, respectively.

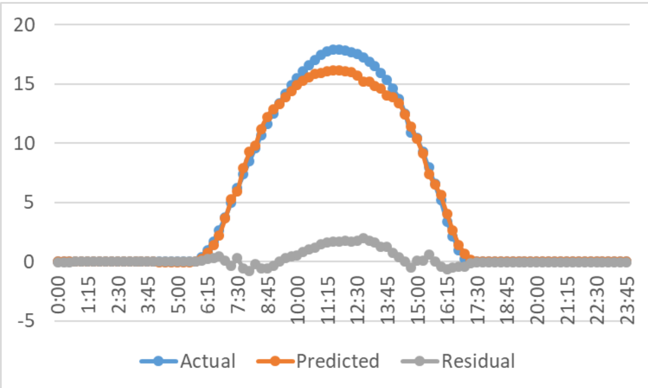

Fig 6. Solar power prediction plot with actual, predicted, and residual point

In addition, Table 1 shows the short term prediction of solar power generation for testing period. In the testing period, MAPE scores of SW-SVR, linear_SVR, RBF_SVR, and Poly_SVR are 24.04%, 74.02%, 18.56%, and 24.16%, respectively. The results vary in the range between 19%–74% approximately, that is between good and poor forecasting. A good forecasting is obtained from RBF_SVR and a poor forecasting from linear_SVR. In addition, the model has been evaluated by using R^2. In testing period, the R^2 scores of SW-SVR, linear_SVR, RBF_SVR, and Poly_SVR are 0.99, 0.97, 0.97, and 0.91, respectively. These results indicate linearity between predicted and actual values. The value of SW-SVR was close to 1 similar to that of the validation period. NRMSE values in testing period for SW-SVR, linear_SVR, RBF_SVR, and Poly_SVR are 8.02%, 9.37%, 9.42%, and 17.35%, respectively. SW-SVR is the best method according to the NRMSE results. The hyperparameter tuning was calculated until the best results were obtained. The parameters C, gamma, and epsilon obtained contribute to the minimization of NRMSE results of the SW-SVR method. The testing error of SW-SWR for C = 32, gamma = 0.01, epsilon = 0.01, and intercept = 128 is obtained for NRMSE of 8.02%. The parameter C was calculated until a steady-state accuracy of training and validation as shown in Fig 4. was achieved. The parameter steady state in range of 10 until 100 appeared in case of the results of hyperparameter tuning was in this range.

In addition to Fig 5., another method that can help to compare and display the quality of predictions is, the residual plot [3]. Fig 6. shows the residual plot between predicted, actual and residual values in the test period of June. From the figure, it is evident that the residual values are centered along the x-axis. Further, outlier values are not found in the image, which implies that the predicted values show good results. In addition, the figure explains the time zone of forecasting for testing data, SW-SVR is closely predicting the solar power, the sky condition as training data made the forecasting matched for time zone before maximum solar power value at noon. In the afternoon, the predicted value missed the maximum data of solar power generation because the results were affected by the weather conditions.

The response variable predicts the solar power generation successfully under all weather conditions by using meteorological measurement. In the future work, essential meteorological data such as clearness index, rainfall, and sunshine duration will be included because it is required to increase the accuracy. Furthermore, by maximizing the classification between sunny, cloudy, and rainy days, we could decrease the significant error.

4 Conclusion and Future Works

In this research, we assessed the performance of SVR methods, such as SW-SVR, linear_SVR, RBF_SVR, and Poly_SVR to predict solar power generation of hybrid power plant in Indonesia. We used ambient temperature, ambient humidity, and solar radiation as explanatory variables. Evaluation of the results was done by statistical metrics such as R^2, NRMSE, and MAPE. SW-SVR predicted solar power generation by using R^2 and obtained a value of 0.99 that is close to 1. Further, the NRMSE score of SW-SVR method is 8.02%, which implies excellent forecasting. Small errors in the result could be due to noisy data, uncompleted data, and missing data. Another evaluation metric MAPE, showed good results for the SVR method with a value of 18.5%.

These results infer that SW-SVR method could be a promising one and can be applied to hybrid power plant in Indonesia. In future works, the algorithm of SW-SVR will be improved by decreasing the error value of the explanatory variables. An alternative to this is to add dataset measurement data such as precipitation, clearness index, and sunshine hours, and consider data from global meteorological measurement and forecast.

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