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Support Vector Regression Method for Predicting Off-Grid Photovoltaic Output Power in the Short Term

Kharisma Bani Adam[1], Desri Kristina Silalahi[2], Bandiyah Sri Aprillia[3], Husayn Aththar Adhari[4]
[1,2,3,4]School of Electrical Engineering, Telkom University
[3]bandiyah@telkomuniversity.ac.id*

Abstract

Photovoltaic (PV) technology is a renewable technology utilizing conversion of solar power or solar radiation into electrical energy. In the manufacture of Solar Power Generation systems, reference is needed regarding the cost of generation and scheduling of maintenance plans. To obtain this reference, it is necessary to predict the photovoltaic power output which is used to determine the power output of PV in the future. In this study, a system that is used to predict short-term power output in PV is designed. This system uses solar irradiation data and 42 days of power output in off-grid PV mini-grid as the dataset. The dataset obtained from the PV output is processed using the Support Vector Regression method with the Kernel Radial Basis Function (RBF) function. Based on the dataset used, this study succeeded in testing the best kernel, namely the RBF kernel. Evaluation of the prediction model obtained a smaller error value than other kernel tests with a Mean Absolute Percentage Error (MAPE) value of 21.082%, Mean Square Error (MSE) value of 0.122, and Mean Absolute Error (MAE) value of 0.262. The prediction model obtained is used to predict the short-term PV power output for the next 3 days. The results of the prediction model have an error value of 5.785 % for MAPE, 0.005 for MAE and 0.069 for MSE. Therefore, the predictive model can be categorized as very good and feasible to predict short-term power output.

Keywords: kernel, photovoltaic, prediction, support vector regression

1. Introduction

Photovoltaic (PV) technology is a renewable technology utilizing conversion of solar power or solar radiation into electrical energy [1]. The utilization of solar radiation energy to produce electrical energy is deemed as a solar power plant. Solar power plants are photovoltaic solar panels that can convert solar energy into electrical energy to convert electricity needs.

The Indonesian government has begun to use alternative energy from sunlight to support the use of new and renewable energy for the electrical needs of public facilities. For example, the use of solar energy for outdoor lighting to have less constraint on budgeting. Indonesia is a tropical country, which means in the future this alternative solar energy can be utilized optimally in various sectors.

Based on statistical data from the International Renewable Energy Agency (IRENA) in 2021, the region that has developed the most renewable energy is Asia, followed by Europe, North America, South America, Eurasian (Europe and Asia region) and others [2]. Renewable energy capacity is expected to continue to increase by more than 8% by 2022, reaching nearly 320 GW [3]. However, unless new policies are implemented quickly, growth remains steady in 2023 as PV mini-grid expansion cannot fully offset hydropower and wind power is steadily lower year-on-year. Meanwhile in Indonesia, the utilization of new and renewable energy is still not optimal. Based on data from the ministry of energy and mineral resources, the use of energy sources is still dominated by fossil energy. To elaborate, petroleum energy sources are still the heart of energy consumption for Indonesia, reaching 43%, with coal energy at 28% and natural gas at 22%, while the use of new and renewable energy has only reached 6.2% [4].

Solar power plants require scheduling for repairs and maintenance. However, PV has a characteristic where absorbed solar energy is inconsistent and intermittent, commonly because the panels are blocked by clouds, rainy weather, and/or other factors which makes power output cannot be known beforehand. Therefore, we need a prediction system in order to have an idea the amount of PV power output for the next few days, this prediction is needed to be able to know when PV

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produces large power output and when PV produces less power in the future. The purpose of predicting power output is important in planning and managing network systems in Solar Power Plants. Forecasting or prediction of power output is an important component in the field of electric power for electrical energy management systems. Precise forecasting helps improve power system reliability, reduce generation costs, and schedule maintenance plans [5].

Prediction of power output in photovoltaic can be done using a prediction method with prediction results based on the desired time period namely short term, medium term, and long term. Research on the prediction of power output in photovoltaics has been carried out by L. Liu [6]. This study used the Back Propagation Neuron Network (BPNN) method with a MAPE value of 7.1% for a 4 days prediction period which has strong predictions, large data error tolerance and excellent mapping capabilities. The Support Vector Machine (SVM) method also produces a photovoltaic prediction model that is better than Linear Regression [7]. This can be seen from the evaluation of the model where the RMSE (Root Mean Square Error) value in the SVM method is smaller than the linear regression. SVM method has also been widely used by combining other methods. This is done to get a more optimal prediction model [7]. One of them is using Hybrid K-means grey Relational Analysis and Support Vector Regression to predict short-term PV power [8]. The results obtained an accurate PV power prediction model with RMSE 0.9608.

The SVM method is able to overcome the problem of overfitting in solving various time series forecasting problems to achieve high generalization performance [9]. The evaluation model used to determine whether the prediction model is appropriate or not is by using an error value. The methods used are Mean Square Error (MSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

In this research, a forecasting model for the PV system is made by predicting the power output produced by photovoltaic in the short term. Photovoltaics can generate electricity from solar cells, which can then be predicted for power output in the photovoltaic system using a machine learning method, namely Support Vector Regression (SVR). In predicting power using Support Vector Regression, the data is taken from solar irradiation and PV power output to be used as a dataset. SVR and Artificial Neural Network (ANN) provide better results than classical regression methods systematically [10]. Although ANN and SVR give the same results for forecasting, SVR is easier to use than ANN. Because that the automatic optimization step is very complex in the case of ANN [10]. ANN uses an optimizer to utilize a neural network with an optimization algorithm, replacing backpropagation with other optimization techniques to solve specific problems [11]. So, optimization technique is needed. Meanwhile, SVR uses the concept of a soft margin loss function by adding a slack variable to overcome imprecise constraints in optimization problems [12]. Furthermore, by using dual problem and quadratic program, the SVR optimization solution can be done [12]. The advantages of the SVR method than ANN is ability to solve overfitting problems. ANN has a weakness in solving overfitting problems so that it will produce lower accuracy. Meanwhile, SVM can solve the problem of overfitting and accuracy rate higher [13]. So, it is recommended to use SVR instead ANN. Search for Support Vector Regression parameters using the Grid Search method. In SVR, using the grid search method can provide increased accuracy of prediction results [14]. Grid search is very suitable for high-dimensional spaces, but can also be used for parallel dimensions, because of the hyperparameter values can be used for variables that are independent of each other [12].

2. Research Methods

The research method used in this study is described in Figure 1 below. In the initial process, it is done by entering training data in the form of solar irradiation and PV power output, then initializing parameters and selecting parameters for SVR. The parameter selection process depends on the SVR method used. The types of training strategies are Epsilon-SVR (ε-SVR) and Nu-SVR (υ-SVR). From the parameters that have been selected, an evaluation of the model is carried out. If the evaluation of the model is appropriate, the prediction model is saved, if not, it returns to the parameter initialization process. The results of a suitable forecasting model will be used to forecast the test data.

2.1 Input Data

The input data used in this study is the power output data generated by solar panels. The design of this system uses two data in the form of solar irradiation data originating from the Telkom University Public Lecture Building and PV power output data from the solar power plant in Telkom University's P building. The input data used is numerical data. The input data are photovoltaic output power for 31 days starting from November 9, 2020 to January 15, 2021.

2.2 Training data and testing data

Training data used to train and develop SVR prediction models. Training data is very important because it is used in building a prediction model that is able to predict the PV output power optimally. The training data used in the form of tabular data consisting of solar irradiation data from the Telkom University public lecture building and PV power output data from the solar power plant in Telkom University's P building.

Both data are taken with an interval of 20 minutes. The dataset used as training data have a duration of 31 days. The analysis was carried out using 1134 samples which were divided into two parts, 80% as training data and another 20% as test data.

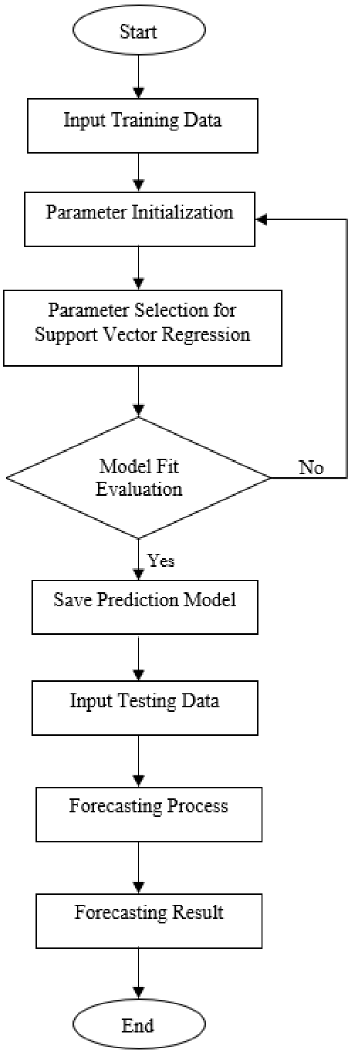

Figure 1. Flowchart

Test data is used to validate the prediction model as well as to predict future data. The test data used are test data within a period of 3 days and the prediction results are validated. This prediction is made as a short-term prediction because it only looks at predictions for the next few days.

2.3 Forecasting Model

The prediction model used in this study is to use Support Vector Regression (SVR). SVR is one of Support Vector Machine (SVM) methods for problems in regression. The result of the regression problem is a real number or continuous. The SVR method can overcome the problem of overfitting to produce good performance [15].

Smola and Scholkopf explains SVR consist of λ training data sets, (x_j, y_j), where j=1, 2, …, λ and $x = \{x_1, x_2, \dots, x_\lambda\} \subseteq R_N$ as input, $y = \{y_1, y_2, \dots, y_\lambda\} \subseteq R_N$ as output. In SVR, the $f(x)$ function will find the actual target that has the largest deviation [15]. Best regression has value is equal to 0. Based on the data, SVR will approximate to find a regression function $f(x)$, minimal complexity, and ε-tolerance error. The regression function $f(x)$ equation is [15]:

$$f\,(x) = w^T \varphi(x) + b \qquad (1)$$

$\varphi(x)$ is a point in the feature space with a higher dimension, the result of the mapping of the input vector x in the input space with lower dimensions. The risk function will be minimized to obtain an estimate of the coefficients w and b

Support Vector Regression (SVR) is a development of SVM to handle regression cases. SVR has two types of training strategies, namely Epsilon-SVR (ε-SVR) and Nu-SVR (υ-SVR) [16]. In ε-SVR, the best estimate of the coefficient value in the function is obtained for the minimal value of ε-insensitive loss function because the low value of ε (read as 'epsilon') indicates a high approximation value [17]. However, this ε-SVR has limitations where the value of ε must be defined before the training process so that problems will arise when dealing with data that is difficult to anticipate between the values of ε. Another strategy is υ-SVR. In this υ-SVR, the shortcomings of ε-SVR can be overcome by limiting the task of finding for quadratic optimization by introducing a new parameter, namely υ (pronounced 'nu') which functions to control the number of support vectors and training errors. The final solution of the SVR predictor is shown in the following equation:

$$f(x) = \sum_{i=1}^{l} (\alpha_i^* - \alpha_i) K(x, y) + b \qquad (2)$$

where $f(x) =$ hyperplane, $\alpha_i^*, \alpha_i =$ data points, langrange multipliers, $K(x_i, x) =$ kernel function and $b =$ bias

Assumption of linearity as a requirement for data mining or machine learning techniques, where the resulting algorithm is limited to linear cases. Kernel method is mapped x data in the input space to a feature space with a higher dimension through ϕ [18].

$$\phi: x \to \phi(x) \qquad (3)$$

The value of $k(x_i, x)$ is a kernel function that shows a linear mapping on feature space. It should be explained here that the value of $k(x_i, x)$ cannot always be expressed explicitly as a combination of α, y, and $\phi(x)$ because in many cases, these variables may be unknown or difficult to calculate.

The determination of the type of kernel is used because the data is nonlinear data, in which a kernel function is needed to map the data in the initial dimension space to the new (relatively higher) dimension space. The types

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of kernels used are Linear Kernel, Radial Basis Function (RBF) Kernel and Sigmoid Kernel. The following explains the types of Kernels [18]:

1) Linear Kernel: $K(x, y) = x.y$
2) RBF Kernel (RBF): $K(x, y) = \exp(-\gamma\|x - y\|^2)$
3) Sigmoid Kernel: $K(x, y) = \tanh(\gamma(x.y) + c)$

x,*y* is a pair of two data from all parts of the training data. The C parameter, which is a constant, is the square of the distance between the x and y vectors. The kernel function is used to substitute the dot product from the old dimension feature to the new dimension in the condition that the data are independent [17]. Usually the cross-validation method (Hstie et al, 2001) is used for kernel function selection. The kernel function will determine the high-dimensional features to search for the hyperplane so that the stage of selecting the right kernel function is very important.

Epsilon SVR is an SVR method that uses epsilon parameter support whose implementation is based on libsvm. There are two independent parameters in the model, namely C and ε. Meanwhile, Nu-SVR uses C parameters and to control the number of supporting vectors. Parameters on the SVR were obtained using the Grid Search approach [19]. The complete Grid Search process requires a long processing time. Therefore, it is recommended to divide the Grid Search method into two stages, namely: Loose Grid Search and Fine Grid Search.

2.4 Model Evaluation

In this study, the prediction model of the obtained Support Vector Regression was evaluated using four measurements, namely: Root Mean Square Error (RMSE), Mean Square Error (MSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The model aims to determine the accuracy of the prediction model. Accuracy is based on the magnitude of the error of the four measurements described below:

2.4.1 Mean Square Error (MSE)

Mean Square Error is one of the methods used to measure the error rate or accuracy of a prediction model. MSE calculation is by squaring the data from the average error [20]. The accuracy of the forecasting results is based on the MSE value. The smaller the MSE value, the more accurate it is. MSE calculation uses the following equation:

$$MSE = \frac{\sum(Y_i - Y'_i)^2}{n} \tag{4}$$

With, Y_i = Actual data, Y'_i = Predicted data dan n = Amount of data

2.4.2 Mean Absolute Error (MAE)

Mean Absolute Error is one of the methods used to measure the level of error or accuracy of a predictive model. The result of MAE calculation is the average absolute error between the forecast result and the actual value [21]. The accuracy of the MAE value forecasting results. The smaller the MAE value, the more accurate it is. MAE calculation uses the following equation:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|f_i - y_i| \tag{5}$$

With, f_i = Predicted value, y_i = Actual value, n = Amount of data.

2.4.3 Mean Absolute Percentage Error (MAPE).

Mean Absolute Percentage Error is an error measurement by calculating the percentage that deviates between the actual data and the predicted data [22]. MAPE calculation uses the following equation:

$$MAPE = \left(\frac{100\%}{n}\right)\sum_{t=1}^{n}\frac{|Xt - Ft|}{Xt} \tag{6}$$

With, Xt = Actual data in t period, Ft = Predicted data or forecast in t period and n = amount of data.

The smaller the MAPE value, the better the model's ability to predict. MAPE has a range of values that can be used as material for measuring the ability of a predictive model, the range of MAPE values can be seen in Table 1 [23].

Table 1. MAPE Value range

MAPE Range	Description
< 10 %	Very Good Model Prediction Results
10 – 20 %	Good Model Prediction Results
20 – 50 %	Decent Model Prediction Results
> 50 %	Bad Model Prediction Results

3. Results and Discussions

3.1 Parameter Selection

This process aims to determine the parameters of the method on the given training data. In SVR with RBF kernel function, two parameters are needed, namely C and γ parameters. Parameter is a parameter used to measure the tradeoff of misclassification of training data and the larger value of parameter means that some training data will have more influence on other training data. The approached method used to obtain the optimal combination of C and γ is the Grid Search approach [24].

The Grid Search approach in finding parameter values is given in a certain range of values. Grid Search Algorithm is a parametric search method combined with model evaluation and cross validation [25]. The range of parameter values used in the Grid Search method are: C with a range of values [0.5, 1, 1.5, 2, 2.5, 3], γ with a range of values [0.01, 0.1, 1] and ε with a range of values [0.01, 0.1, 1, 10, 100] [25].

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3.2 Prediction Model

The prediction model built by the SVR method is based on parameter selection to obtain an optimal prediction model. The optimal prediction mode is based on the error magnitude of the SVR prediction model. This can be seen from Figure 2 to Figure 4. The graph of the actual data and the results of the prediction data using the Linear Kernel, RBF Kernel and Sigmoid Kernel functions can be seen. Based on the picture of the PV power forecasting results, it can be seen that there is a significant difference between the actual data and the predicted data. Figure 2 describes the results of forecasting with the SVR method using the Linear Kernel function, there are power fluctuations that occur for each actual data. Predictive power is also close to actual power. Similarly, in Figure 3, the prediction results using the SVR method using the RBF Kernel function show that the predicted power results are close to the actual power. Likewise, Figure 4 is the result of prediction with the SVR method using the Sigmoid Kernel function. In general, the results of the predictive power using the three Kernel functions are close to the actual power that distinguishes the evaluation model.

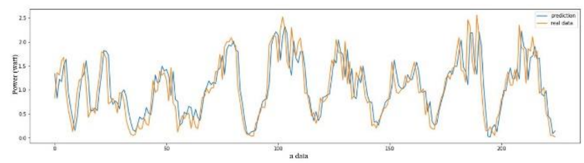

Figure 2. Forecasting Model Using Linear Kernel Function

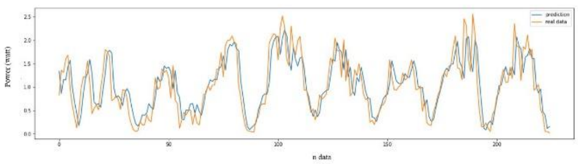

Figure 3. Forecasting Model Using RBF Kernel Function

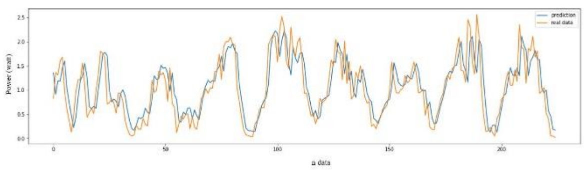

Figure 4. Forecasting Model Using Sigmoid Kernel Function

From the graph of the actual data and data acquisition, the magnitude of the error value is stated in Table 2.

Table 2. Error Value Comparison

Kernel Function	MAPE	MSE	MAE
Linear	21,090%	0,126	0,262
RBF	21,082%	0,122	0,262
Sigmoid	21,836%	0,125	0,269

Based on Table 2, the RBF Kernel function obtained the smallest MAPE value of 21.082%, MSE value of 0.122, and MAE value of 0.262. In other words, the best kernel functions use RBF kernel testing. This is also supported by the score value on testing each Kernel function.

3.3 Prediction Results

The forecasting model is formed by selecting the optimal parameters, then the photovoltaic output power prediction is made using these parameters to predict within a predetermined time period. The selection of the Kernel function based on the best score can be seen in Figure 5. Figure 5 shows that the highest score is the RBF Kernel. Due to RBF Kernel producing the highest score, RBF kernel will be used for the prediction model.

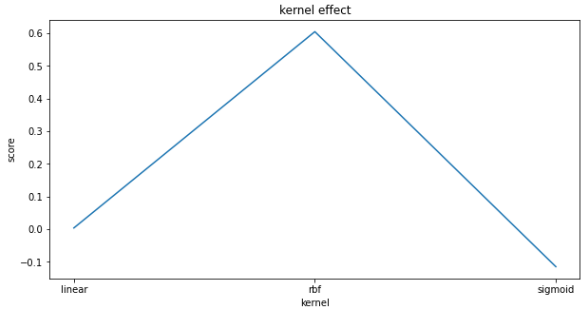

Figure 5. Kernel Function Comparison

The RBF Kernel function is used to form a predictive model, so that parameter selection is then carried out. The results of the search for C parameter are shown in Figure 6. Based on Figure 6, it can be seen that the optimal C parameter with the value of C = 1 with a score of 0.6. Parameter C is a parameter to determine how much deviation. In Figure 7, the value of the γ parameter is obtained, namely on a scale with a score of 0.6. Scale is a value that uses 1/(n_features*X.var()). γ parameter is a parameter that affects the training data. Meanwhile, ε parameter is 0.1 with a score of 0.6 shown in Figure 8. while $\in$ parameter is a parameter to control the width of the regression zone in data processing.

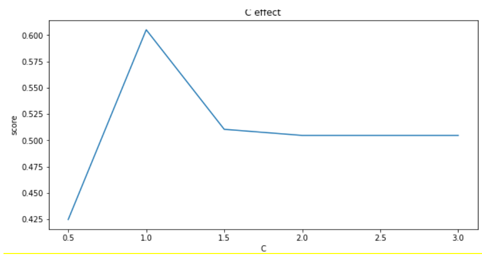

Figure 6. C Parameter results

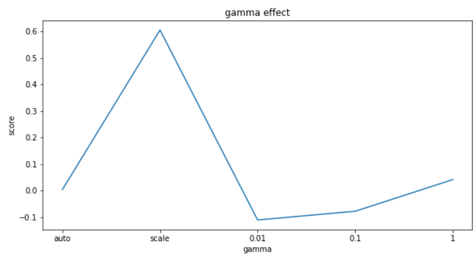

Figure 7. γ Parameter results

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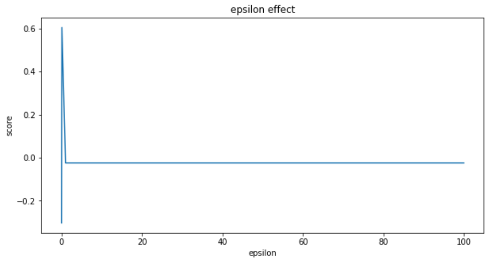

Figure 8. ε Parameter Results

Furthermore, predictions are made using the obtained SVR model along with the parameter values for the RBF Kernel function, namely C=1, γ =scale and ε=0.1. The prediction made is that the PV output power for 3 days was compared with the prediction results with the actual value in order to find out the magnitude of the error obtained.

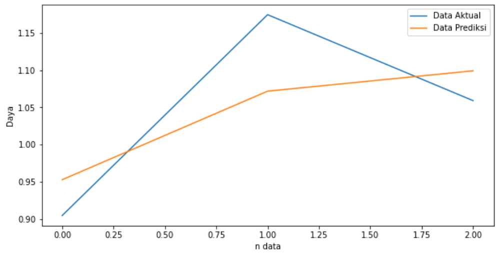

Figure 9. Comparison of Actual and Predicted PV Power Output for the Next 3 Days

Figure 9 shows a graph that compares the actual and predicted PV power outputs very well. Evaluation of the prediction model used has a MAPE value of 5.785 %, indicating that this model is very good and feasible to predict PV power output for the next 3 days because the MAPE value is in the range of 20%. The MAE value is 0.004 and the MSE is 0.069. This model is considered very good for predicting the next 3 days.

Prediction model using Support Vector Regression with RBF Kernel function in predicting PV output power is expected to be able to provide information for planning and managing network systems in Solar power plants.

4. Conclusion

The conclusion in this study is that the Support Vector Regression prediction model with the Kernel Radial Basis Function (RBF) function obtained evaluation results in a good category. The model is good and feasible for predicting photovoltaic power output. This can be seen from the evaluation of the prediction model with error value smaller than other kernels tested with Mean Absolute Percentage Error (MAPE) value of 21.082%, Mean Square Error (MSE) value of 0.122, and Mean Absolute Error (MAE) value of 0.262. With the prediction model obtained, it can be used to predict the short-term PV output power for the next 3 days. The results of the prediction model have an error value of 5.785 % for MAPE, 0.005 for MAE and 0.069 for MSE. Therefore, the prediction model can be categorized as very good and feasible to predict short-term power output. Suggestions for further research can use the SVR method for long-term. Furthermore, it requires a lot of datasets for long term prediction until 1 year. In addition, it can also use other forecasting methods such as Random Forest.

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