**TELKOMNIKA Telecommunication, Computing, Electronics and Control**
Vol. 18, No. 2, April 2020, pp. 1089~1094
ISSN: 1693-6930, accredited First Grade by Kemenristekdikti, Decree No: 21/E/KPT/2018
DOI: 10.12928/TELKOMNIKA.v18i2.14816


# Short-term photovoltaics power forecasting using Jordan recurrent neural network in Surabaya

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**Article Info**

***Article history:***

Received Jul 19, 2019
Revised Dec 25, 2019
Accepted Feb 19, 2020

***Keywords:***

Forecasting
JRNN
Photovoltaic

**ABSTRACT**

Photovoltaic (PV) is a renewable electric energy generator that utilizes solar energy. PV is very suitable to be developed in Surabaya, Indonesia. Because Indonesia is located around the equator which has 2 seasons, namely the rainy season and the dry season. The dry season in Indonesia occurs in April to September. The power generated by PV is highly dependent on temperature and solar radiation. Therefore, accurate forecasting of short-term PV power is important for system reliability and large-scale PV development to overcome the power generated by intermittent PV. This paper proposes the Jordan recurrent neural network (JRNN) to predict short-term PV power based on temperature and solar radiation. JRNN is the development of artificial neural networks (ANN) that have feedback at each output of each layer. The samples of temperature and solar radiation were obtained from April until September in Surabaya. From the results of the training simulation, the mean square error (MSE) and mean absolute percentage error (MAPE) values were obtained at 1.3311 and 34.8820, respectively. The results of testing simulation, MSE and MAPE values were obtained at 0.9858 and 1.3311, with a time of 4.591204. The forecasting has minimized significant errors and short processing times.



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## 1. INTRODUCTION

In renewable energy, PV gets a lot of attention to replace fossil-fueled plants [1, 2]. Because PV uses solar energy to generate electrical energy. PV systems have environmental benefits, and have low maintenance costs [3] moreover PV can increase the reliability of the electric power system [4]. However, the investment costs of PV are expensive and the value of PV power efficiency is low. PV power efficiency values are affected by solar radiation, temperature, and conditions of the PV panel [5, 6]. Solar radiation and temperature cannot be determined with certainty. Therefore, PV power forecasting is very necessary for predicting the power generated by PV so that the load can be supplied to the maximum.

There are several methods for predicting short-term power such as using Artificial Neural Networks (ANN) [7, 8], Support Vector Machine (SVM) [9] with solar radiation parameters, temperature, and other environmental parameters [10, 11]. However, ANN does not have feedback so that the output of ANN can be corrected and get optimal results. As for SVM, kernel function and loss functions are difficult to get optimal results [12]. Therefore, accurate and fast PV power forecasting methods are needed so that intermittent PV power can be overcome.

In this paper, short-term PV power forecasting is carried out using the JRNN method. JRNN method is the development of the ANN method. JRNN has 2 steps, namely training and testing steps. The training step consists of forward and backward operations. The difference between JRNN and ANN are the feedback output from each ANN layer to the context layer [13]. The backward operation will correct the output of each layer so that the error value from the JRNN prediction result is smaller. The parameters used in this short-term PV power forecasting are temperature and solar radiation from April until September in Surabaya Indonesia. In general, the temperature and solar radiation datas used are data in the dry season that occurs for six months.

## 2. RESEARCH METHOD

### 2.1. PV model

In this case, the PV module used has characteristics such as Figure 1 and Figure 2. Mathematically, the current and voltage characteristics generated from a solar cell with ideal conditions (temperature 25°C and irradiance 1000W/m$^2$) are like (1) [14]. Thus, for a PV panel that practically consists of various components [15], the current and voltage characteristics generated mathematically are like (2):

$$I = I_L - I_0\left[exp\left\{\frac{q(V + I.R_S)}{n.K.T}\right\} - 1\right] - \frac{V + I.R_S}{R_{SH}} \tag{1}$$

$$I = N_P.I_L - N_P.I_0\left[exp\left\{\frac{q(\frac{V}{N_S} + I.\frac{R_S}{N_P})}{a.n.K.T}\right\}\right] - \frac{V.\frac{N_P}{N_S} + I.R_S}{R_{SH}} \tag{2}$$

where,

$I$ = output current (ampere)
$I_L$ = the current produced by photovoltaics (ampere)
$I_0$ = reverse saturation current (ampere)
q = element load, 1.6 * 10-23 C
V = voltage between output terminals (volt)
$R_S$ = series resistance (ohm)
n = ideal diode factor (range 1-1.75)
K = Boltzmann constant, 1.38 * 10-19 J/K
T = absolute temperature
$R_{SH}$ = resistance shunt (ohm)
$N_P$ = the number of photovoltaics connected in parallel
$N_S$ = the number of photovoltaics connected in series

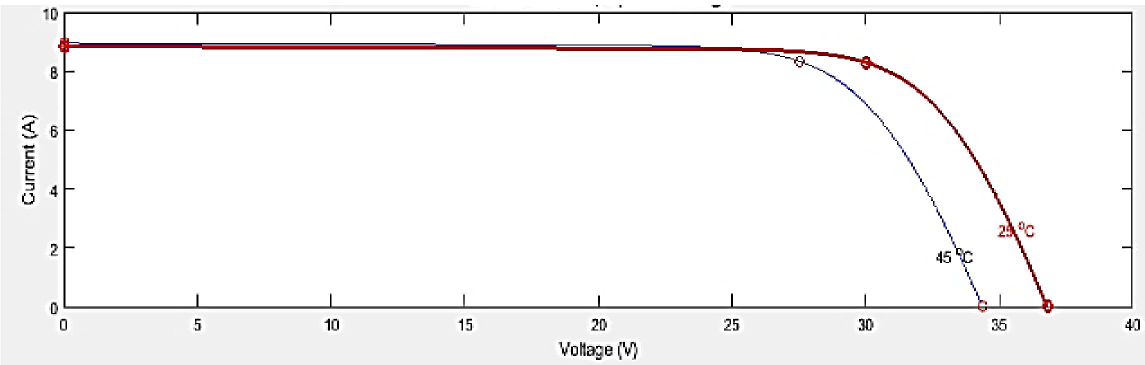


Figure 1. I-V PV characteristics [16]

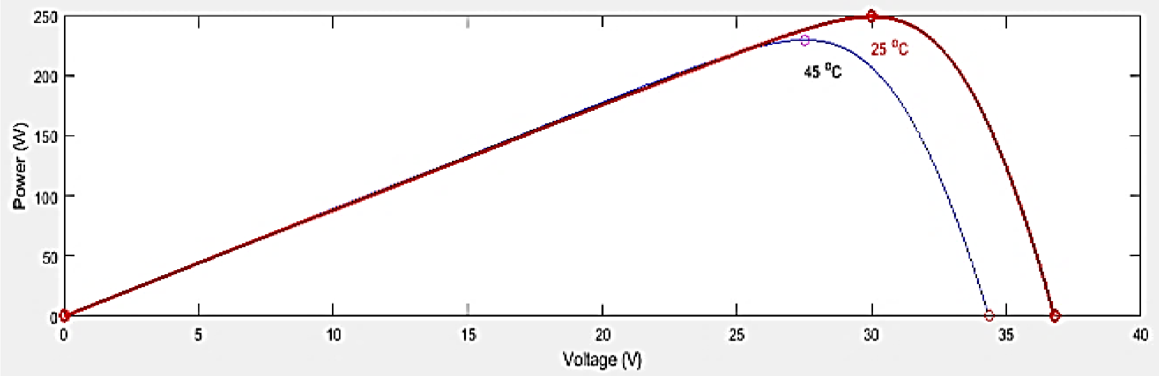


Figure 2. P-V PV characteristics [16]

### 2.2. Jordan recurrent neural network (JRNN)

JRNN is the development of ANN [17]. In this paper, JRNN is used to predict PV power with input parameters such as temperature and solar radiation in Surabaya. Temperature and solar radiation data were obtained from April to September. JRNN has the training and testing step [18]. In the training step, there are two operations namely forward operation and backward operation. Forward operation is used to enter temperature and solar radiation data and calculate PV power through the hidden layer to produce the output layer. Then backward operation, the output layer results are put back into the delay block, and context layerto get the final output [19-21]. Figure 3 is a diagram of JRNN and the input, output, context layer, number of hidden layer, and delay block are $u(k-1), y(k)$, $y(k-1), K$, and $q^{-1}$, successively. The model from JRNN based on Figure 3 has equations like (3) and (4). Let $w_{i,0}^{(1)}$ and $w_0^{(2)}$ are weights of the first and second layer, respectively. Then, $\varphi$ is nonlinear transfer function.

$$y(k-1) = w_0^{(2)} + \sum_{i=0}^{K} w_i^{(2)} \varphi(z_i(k)) \tag{3}$$

$$z_i(k) = w_{i,0}^{(1)} + w_{i,1}^{(1)} u(k-1) + w_{i,2}^{(1)} y(k-1) \tag{4}$$

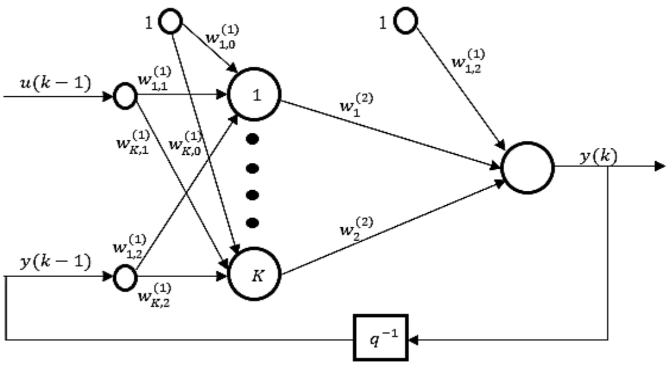


Figure 3. Block diagram of JRNN

JRNN has 3 hidden layers implemented, the number of the first to the third hidden layers are 12, 5, 1, respectively [22]. In the input layer, the number of neuron units are 2 and 2 neurons are entered solar radiation and temperature data. Then, another neuron was an offset neuron which always produces a value of 1 [23]. The number of output layers is 1. The output layer produces PV power forecasting every month in the next month. The epoch is used as the number of iterations, which is 1000. And allowed error reward was set to 10-4. After all neural networks are trained, the next step is testing step. Testing step is done to test PV power forecasting capabilities. Then, the results of the testing step are compared with the actual PV power in July. The main differences between JRNN and ANN are shown in Figure 4 and Figure 5, severally.

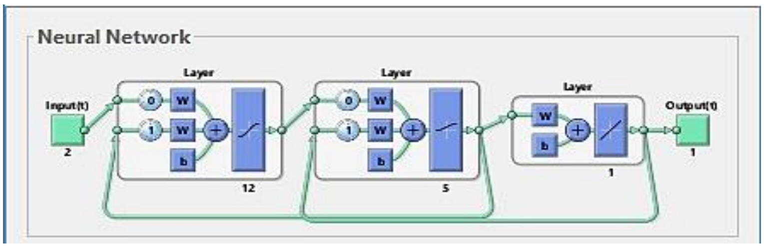


Figure 4. Design of JRNN

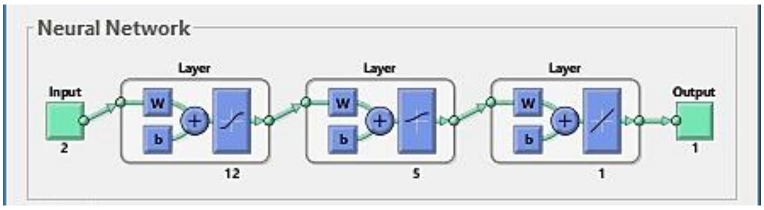


Figure 5. Design of ANN

In JRNN and ANN, PV Power forecasting results are evaluated with the Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE). The MSE and MAPE are references for measuring errors from trained models. If the MSE and MAPE values are lower, the resulting model is better and more accurate. The equation (5) and (6) are equation of Sum of Square Error (SSE) and MSE, successively [24]. Where, $n$ is the number of the data processed and observed. Then, $Y'$ and $Y$ are the predicted and actual value, severally.

$$SSE = \sum_{1}^{n} (Y'_{t-k} - Y_{t-k})^2 \tag{5}$$

$$MSE = \frac{SSE}{n} \tag{6}$$

## 2.3. Data preparation

This study used solar radiation and temperature data in the Surabaya area. Data retrieval was carried out from April to September. The data recording was carried out every 30 minutes for 24 hours [25]. Figure 6 and Figure 7 are samples of data from solar radiation and temperature for 24 hours, respectively.

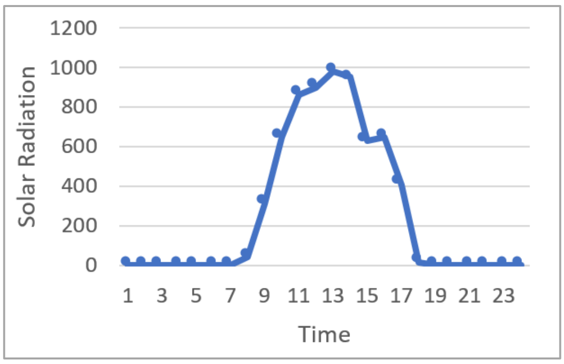


Figure 6. Sample of data from solar radiation

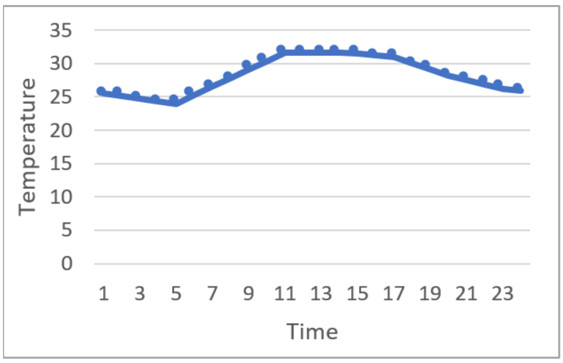


Figure 7. Sample of data from temperature

## 3. RESULTS AND ANALYSIS

Figures 8 and 9 are the prediction of PV power with the JRNN and ANN method. The pictures are arranged side by side with the actual data. From the prediction results, the JRNN method has succeeded in producing the expected PV power predictions. In fact, the results of JRNN and ANN are almost the same. The resulting prediction approaches the actual data from the PV power produced. However, there are some disadvantages that are generated by ANN. This can be seen in Table 1. Table 1 shows that JRNN has smaller MSE and MAPE values than ANN. This shows that the predictions produced by the JRNN are closer to the actual data. So that the JRNN can be said to be more accurate because JRNN has a low error rate. Besides that, the time needed for the JRNN to produce these predictions is longer than ANN.

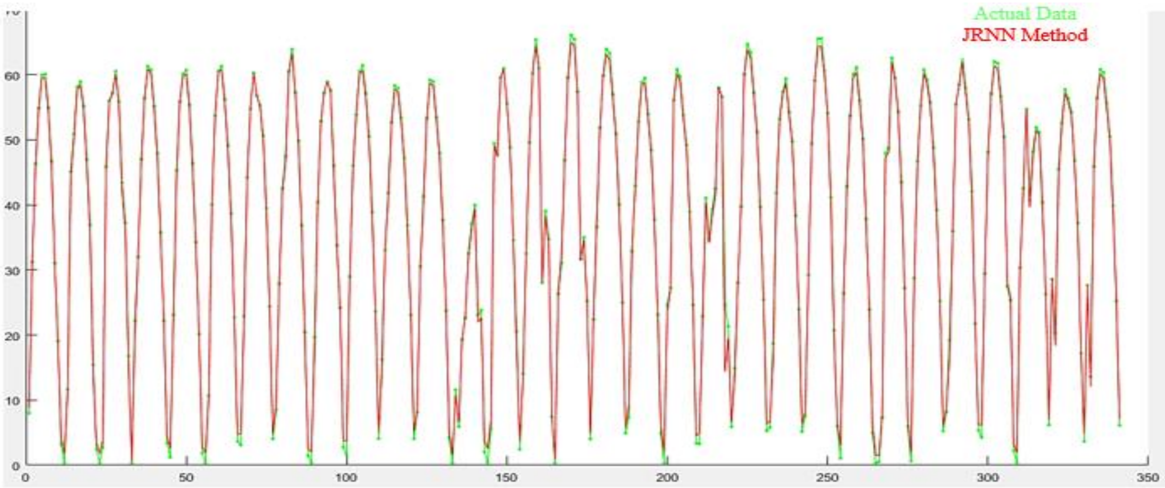


Figure 8. The prediction of PV power with the JRNN

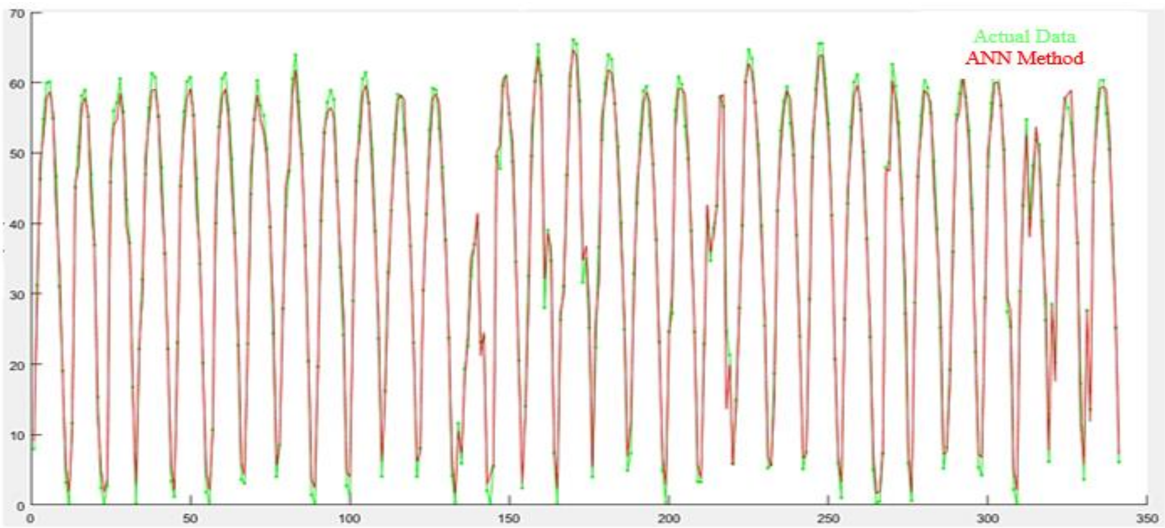


Figure 9. The prediction of PV power with the ANN

Table 1. MSE, MAPE and time of the test result

| JRNN | | | | | ANN | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Training | | Testing | | Time | Training | | Testing | | Time |
| MSE | MAPE | MSE | MAPE | | MSE | MAPE | MSE | MAPE | |
| 2.1180 | 34.8820 | 0.9858 | 1.3311 | 4.591204 | 3.1077 | 40.0600 | 4.2425 | 2.0838 | 4.361669 |

## 4. CONCLUSION

PV power predictions have been successfully carried out with the JRNN method, which gives low MSE and MAPE values. because the lower the MSE and MAPE, the predictions generated can be close to the actual data. The MSE and MAPE generated in the training step are 2.1180 and 34.8820, respectively. then the MSE and MAPE generated in the testing steps are 0.9858 and 1.3311, respectively. and the time needed is 4.591204. Predicted results from JRNN are more accurate than ANN. However, the time taken is longer.

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