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Advanced Extreme Learning Machine for An Hour PV Forecast Using General Weather Data

***Abstract:** In recent years, Indonesia has placed great attention on the use of renewable energy resources as a way to decrease gas emission. Located at the equator, Indonesia has many advantages in renewable energy resources, especially photovoltaic (PV). Photovoltaic offers a big opportunity to contribute to the power grid, yet it also comes with its challenges. The use of PV involves a major uncertainty as the inputs of PV are weather conditions that are constantly changing. With Indonesia planning to penetrate the PV farm into the power grid, it is necessary to be able to generate an accurate forecast to assist the power grid control operator. Many algorithms are applied to obtain a precise and accurate PV power generation. One of the algorithms generally used by researchers is the conventional back propagation neural network. It is one of the most commonly applied algorithms, yet it also has a complex setting and numerous parameters. To help overcome this issue, extreme learning machine (ELM) is applied alongside with backpropagation neural network (BPNN), resulting in a more promising result. However, the random value for ELM parameters has become another problem of its own. This paper discusses an advanced ELM to obtain a better PV forecast result. The combination of PV input, ambient temperature, global tilted irradiation (GTI), wind direction, wind velocity and humidity are applied on the kernel extreme learning machine (K-ELM). We found that K-ELM proposes a better performance compared to ELM in facing a nonlinear data, along with better learning capability, mapping ability, and an improved efficiency. We also developed the input data using BPNN, ELM and support vector machine (SVM) to compare training, testing and calculation time.*

***Streszczenie.** W ostatnich latach Indonezja przywiązywała dużą wagę do wykorzystania odnawialnych źródeł energii jako sposobu na zmniejszenie emisji gazów. Położona na równiku Indonezja ma wiele zalet w zakresie odnawialnych źródeł energii, zwłaszcza fotowoltaiki (PV). Fotowoltaika daje duże możliwości wniesienia wkładu w sieć energetyczną, ale wiąże się również z wyzwaniami. Korzystanie z PV wiąże się z dużą niepewnością, ponieważ wejścia PV to stale zmieniające się warunki pogodowe. Ponieważ Indonezja planuje penetrację farmy fotowoltaicznej do sieci energetycznej, konieczne jest wygenerowanie dokładnej prognozy, aby pomóc operatorowi kontroli sieci energetycznej. W celu uzyskania precyzyjnego i dokładnego wytwarzania energii PV stosuje się wiele algorytmów. Jednym z algorytmów powszechnie stosowanych przez badaczy jest konwencjonalna sieć neuronowa wstecznej propagacji. Jest to jeden z najpowszechniej stosowanych algorytmów, ale ma też złożoną nastawę i liczne parametry. Aby rozwiązać ten problem, zastosowano ekstremalną maszynę uczącą (ELM) wraz z siecią neuronową z propagacją wsteczną (BPNN), co daje bardziej obiecujący wynik. Jednak losowa wartość parametrów ELM stała się kolejnym problemem. W niniejszym artykule omówiono zaawansowane ELM w celu uzyskania lepszego wyniku prognozy PV. Kombinacja sygnału wejściowego PV, temperatury otoczenia, napromieniowania globalnego odchylenia (GTI), kierunku wiatru, prędkości wiatru i wilgotności jest stosowana na maszynie ekstremalnego uczenia jądra (K-ELM). Odkryliśmy, że K-ELM proponuje lepszą wydajność w porównaniu do ELM w obliczu danych nieliniowych, a także lepszą zdolność uczenia się, zdolność mapowania i lepszą wydajność. Opracowaliśmy również dane wejściowe za pomocą BPNN, ELM i maszyny wektorów nośnych (SVM) w celu porównania czasu szkolenia, testowania i obliczeń. (**Zaawansowana maszyna ucząca się w trybie ekstremalnym do godzinnej prognozy fotowoltaicznej z wykorzystaniem ogólnych danych pogodowych**)*

Keywords: Photovoltaic, forecast, NN, SVM, and K-ELM.
Słowa kluczowe : Fotowoltaika, prognoza, NN, SVM i K-ELM.

Introduction

Over the past few decades, global warming crisis has made a significant impact on the electricity system. Existing generators in almost every country in the world are required to slowly reduce the use of fossil fuel generators. This is necessary in order to reduce CO2 emissions produced by fossil fuel generators. Countries are competing to use renewable energy sources (ReS) as an alternative energy source. However, with the large number of fossil fuel generators, it is certainly not an easy task to replace them with ReS in a short period of time. ReS also carry a high uncertainty of power output. This would require a strict calculation and precise forecasting of ReS output as it plays an important role in the process of reducing fossil fuel sources. It is expected that ReS can gradually reduce and replace the role of fossil fuels in the existing electrical system.

In Indonesia, the most reliable ReS is PV. Considering that Indonesia has a long summer (6 months) and a nearly balanced ratio of day and night of 12 hours each, it is a great opportunity for Indonesia to apply and benefit from ReS in the existing power grid. Penetrating PV into the power grid would be beneficial and essential, but it would also require great preparation and calculation. If the PV output has high uncertainty, it could create other problems and would lead to bigger issues [1]. The prediction of PV output is, therefore, a crucial matter and must be well-calculated.

Researchers previously used PV output with various range time interval as references, while local weather data was also opted by others [2]. Various range time interval arises due to the input data for PV forecast [3, 4]. Numerical Weather Predictions (NWP) are also used by several authors to obtain the most reliable PV forecast.

To increase the accuracy of the prediction result, many methods have been approached and tested by researchers. One of the methods include statistical methods such as autoregressive integrated moving average (ARIMA) [11], auto-regressive integrated moving average (SARIMA) [12], regression [13], moving average (MA) and autoregressive moving average (ARMA) [14]. One of the disadvantages of the statistical methods is its dependency on historical data trend, resulting in a longer processing time. However, this is necessary because if the mathematical method and parameter adjustment are not synchronized, it will affect the result.

Recently, artificial intelligence has also been used and integrated in the forecasting process of PV output such as artificial neural network (ANN) [15,16], bayesian artificial neural network (B-ANN) [18], support vector machine (SVM) [20,21], constructive neural network [22], extreme learning machine (ELM) [23,24], deep convolutional neural network [25], analog ensemble method [26], focus on output power [27], fuzzy field oriented control [28], and hybrid deep learning approach [29].

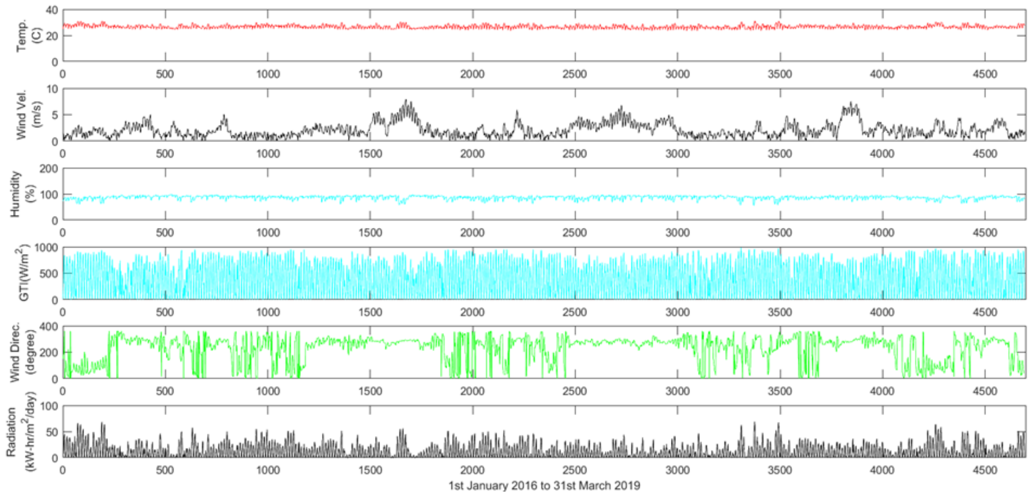

Fig 1. Data Input

This paper proposes an extension of ELM, namely the kernel extreme learning machine (K-ELM) which is an extension of the standard ELM by using the kernel function. This version of advanced ELM offers a more powerful function in predicting PV output. Outcome from the proposed learning algorithm is compared with results from standard ELM, SVM and NN. The performance of these methods is further measured by root mean square (RMSE), mean absolute error (MAE) and mean square error (MSE). Contributions of this paper are as follows:

i. A better forecast result using K-ELM is compared to ELM, SVM, LVQM back propagation and BR back propagation.
ii. We also compare the CPU time process. This is necessary to be used for the real – time data. In this research, the real – time data is processed from historical data.
iii. By selecting the best K-ELM parameters, we can obtain a better result for simulation.

The manuscript is organized as follows. Section 1 is introduction; historical data collecting is explained in section 2. Our computational process and method are described detail in section 3. Section 4 provides simulation result and comparison. In the end, conclusion is accompanied in section V.

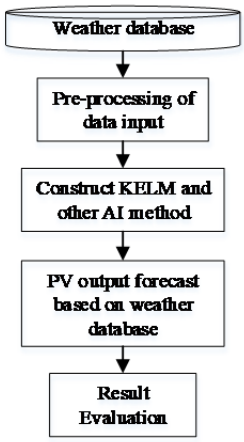

Fig. 2. Flowchart process of PV output forecasting

Historical Data Collecting

Indonesia is generally divided into two seasons only, dry, and rainy. This condition provides an almost balanced data between daytime and night-time. The data used in this research is daytime data specifically from 06.00 a.m. to 05.00 p.m. as there are no power output data after 05.00 p.m.

We used an hourly data in the forecasting process since the available weather data is one-hour interval data only. Figure 1 shows the data in a graph with a significant different of range. A total of 4693 data recorded from 2016 to 2019 were used in this research for the training and testing processes. The available data have one-hour intervals with details as follows: (a) ambient temperature T (°C), (b) global tilted irradiation (GTI), (c) wind direction (°), (d) wind velocity v (m/s) and (e) humidity (%). Further data processing is shown in section 3.

Computational Process

A. Step 1: Pre-processing Data

The PV output forecast is completed in five sequences as shown in figure 2. In step 1, we chose reliable data from the data bank and used three-month data set for training and one-month data set for testing. Data from January-March in 2016 until 2018 are used as training data while that of 2019 are used as testing data. However, before initiating any further processes, we prepared the data by performing data normalization since the input range are significantly different, and it is necessary to use the same number. The normalization process uses the prestd function, while the denormalization in the output process uses the poststd function.

B. Step 2: K-ELM set up

After completing step 1, a new normalization data is ready to be trained and tested. All weather data are built for 1 hour intervals. The data are divided into two, with 80% used for training and 20% for testing. Data from January until April in 2016-2018 is used as training dataset, while data from January until April in 2019 is used as testing dataset.

There are five data input and one target output. As previously mentioned, the data input was processed and converted into the same range value using high dimensional features on radial basis function (RBF) kernel. The K-ELM parameters are subsequently adjusted to find the best result. Further details of the process will be presented in the next chapter. We applied and compared the input data with conventional neural network (NN), SVM and conventional ELM.

C. Step 3: PV power output forecasting

In this section, we describe the weather data conversion to PV output power. Based on the data, the ambient temperature, global tilted irradiation (GTI), wind direction, wind velocity and humidity have a direct impact on the radiation and PV output power [30]. The conversion efficiency of PV can be expressed as follows:

(1) $P_{out} = A \,.\, I \,.\, \eta$

where, A is the PV size (m^2), I is the intensity of radiation for a PV (kw/m^2), and η is a constant value for conversion rating. The formula of η value is defined in (2),

(2) $\eta = \eta_0\,[1 - \gamma(T_0 - T_\gamma)]$

where, T_γ is the temperature reference (24,85°C), η_0 is the conversion efficiency value (12,88); γ is a constant value for temperature coefficient, usually between 0.003/°C until 0.005/°C [30]. The constant value is determined based on the data bank.

D. Step 4: Result comparison

To show that the proposed method produces a better result, we compared results from NN, SVM and conventional ELM. In the training process, we tested 4 different training methods. The aim is to obtain the smallest statistical error value. We proposed the use of K-ELM and compared it with conventional ELM. In addition to getting a small statistical error comparison value, the proposed method also provides a comparison of the data processing time in the training and testing phase. Conventional NN with Levenberg-Marquardt backpropagation (LVQM BP) and Bayesian Regularization Backpropagation (BR BP) training method are also used to compare results. By using two conventional NN methods, it is expected to find the statistical error with the smallest value. Based on references stated in section 1, ELM has a faster CPU time than conventional NN. As a final step, the statistical error value is also compared to the value from SVM method. The accuracy of the statistical error value is the main key.

Extreme Learning Machine

ELM is a training method that has a single layer and only performs feedforward networks [23-24]. Figure 2 shows the architecture of ELM where it involves three layers of network structure. In general, the first layer is the input layer, while the second is the hidden layer, and the third is the output layer. ELM training and testing are very similar to single feedforward network (SLFN) algorithm. However, SLFN has a longer mapping process, while ELM offers a shorter mapping process to connect the input and output data. ELM was developed to overcome the shortcomings of conventional NN in the training and testing time. It is necessary to determine the network parameter, and in the process, this parameter shall be updated in the iteration phase.

Therefore, it takes a longer CPU time to update the NN parameter and perform the mapping process from the beginning. As previously stated, ELM was developed to shorten the CPU time and produce a better mapping in input and output relation. By using ELM, it is possible to have a faster timing process while producing a more accurate prediction. However, we found a weakness in the ELM mapping process. Values of weight and bias in the hidden layer of ELM were determined randomly. Hence, the user must go through a series of trial-and-error calculation to obtain an adequate result. The kernel function in ELM is, therefore, necessary to minimize the random value and shorten the trial-and-error process.

The detail formula is presented as follows. x_i=$[x_{i1}, x_{i2}, \ldots, x_{iN},]$ $\in$ R^n is the vector input data with dimension N. $\hat{y}_{out}$ is the output value in vector. [31] present an ELM model,

(3) $\hat{y}_{out} = \sum_{i=1}^{M} \beta_i . g_i(w_{ij} \,.\, x_{iN} + b_j)$

Where $w_i = [w_{i1}, w_{i2}, \ldots, w_{ij}]$ is the value of weight input. This value is represented the connection between N input neurons to jth neurons in the hidden layer. b_j is the bias value of jth in the hidden layer. $g_i(.)$ is the activation function. $\beta_i = [\beta_1, \beta_2 \ldots \beta_M]$ is weights value on the output layer. It is describing the connection from i neurons in the hidden layer to M number of neurons in the output layer. The goal of ELM is to obtain a small error between data target and ELM result. Also, ELM has a faster process than feedforward neural network and has a better performance.

In other formula, it can be defined as:

(4) $Min_{H,\beta} = ||H\beta - T||, ||\beta||$

Which,

(5) $\beta = H^T(\frac{1}{C} + HH^T)^{-1}T$

where H is the hidden output, C is the coefficient of regularization, and T is the predicted output or target output. If formula (8) and (9) are combined to (6), the output of ELM will be defined as follows.

(6) $\hat{y}_{out} = H^T(\frac{1}{C} + HH^T)^{-1}T.\, g_i(x_{ij})$

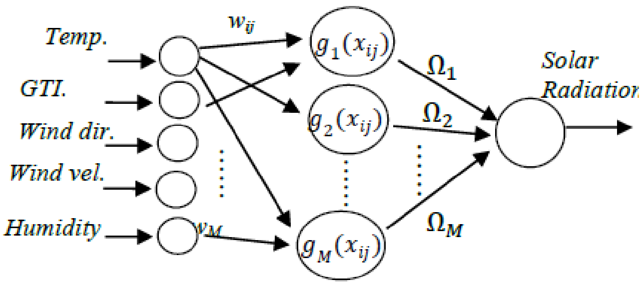

Fig. 3. ELM Architecture

The Implementation of Kernel Extreme Learning Machine (K-ELM)

In order to increase the ELM performance, K-ELM was developed to help improve the generalization network. The mapping feature must also be upgraded to acquire better and more precise results.

We defined a kernel formula,

(7) $\{\Omega_{ELM} = HH^T = g(x_i).\, g(x_j)\; K(x_i, x_j)$

(8) $K(x_i, x_j) = exp(\frac{||x_i - x_j||^2}{2\sigma^2})$

where σ is kernel width, generally known as kernel parameter. This parameter will affect the K-ELM result; hence, the best value must be selected.

The output of ELM with kernel will be,

(9) $\hat{y}_{out} = [K(x_i, x_j)](\frac{1}{C} + HH^T)^{-1}T$

The performance of error calculation in K-ELM depends on σ value and C value. A comparison with SVM will be shown in the next section. It is necessary to compare results with NN, SVM and conventional ELM to highlight the ways in which K-ELM exceeds in terms of speed and the stability of its structure. A more detailed explanation on the process of how K-ELM reaches the results will be discussed in the following section.

K-ELM method has the same phases as NN, SVM and conventional ELM. In the K-ELM method, it is necessary to conduct training process on solar PV forecast. Below is the detailed process of K-ELM through step 1 until step 4:

a. Select and normalize the data input, ambient temperature, GTI, wind direction, wind velocity, humidity, and solar irradiation. Solar irradiation is set as target.
b. Divide data set into training and testing data, we use 80% data for training and 20% data for testing.
c. Convert the data using (8) to perform the kernel function in high dimensional function.
d. Determine the σ value and C value as K-ELM parameter.
e. Conduct the training phase in which we used formula (1) – (9) to calculate the PV forecast.
f. Then, the next step is obtaining the error calculation using MAE, RMSE and MSE.

After completing the training process, the next step is conducting the testing process in the following order:

1. Collect testing data from dataset previously stated.
2. Use the same σ value and C value as the training process.
3. Perform data normalization for the testing data to be used as data input for K-ELM.
4. Conduct the c point process same as the training phase.
5. Calculate the PV forecast using K-ELM method.
6. Deformalize the output value is necessary before calculating the error value.

The last step is calculating the statistical error value in the testing process.

Statistical Error Calculation

The statistical error calculations used in this research are commonly used in the forecasting processes, namely the root mean square error (RMSE), mean absolute error (MAE), and mean square error (MSE).

The following is the statistical error method used as evaluation,

(10) $$MAE = \frac{\sum_{i=1}^{N} |\hat{y}_i - y_i|}{N}$$

(11) $$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(\hat{y}_i - y_i)^2}{N}}$$

(12) $$MSE = \frac{1}{N}\sum_{i=1}^{N} (\hat{y}_i - y_i)^2$$

where *N* is number of datasets, $\hat{y}_i$ is prediction result, and y_i is measurement data. This statistical error value is used in both the training process and testing process. This research aims to find the smallest statistical error value in the four methods used

Result and Discussion

In this research, MATLAB is used in running the data for the training and testing processes. While for conventional NN, MATLAB NN toolbox is used with parameter settings as shown in table 1.

The parameters used in each method are presented in table 1. These parameters are acquired from the comparison of the smallest statistical error values between the four methods used in this research. The statistical error value is also used in the training and testing process. To produce these parameters, the researcher periodically conducted several trial-and-error calculations. The calculations were carried out by changing the value of each parameter to find the smallest statistical error value in all statistical error evaluation methods.

Table 1. Optimal Parameters for PV Forecast

K-ELM	ELM	SVM	LVQM BP	BR BP
γ= 100 C= 30	Hidden Neuron = 200	C= 20 σ=0.0009	Hidden Neuron = 100	Hidden Neuron = 200

Training Process

This section presents the training processes of the three methods used in this research. The main objective of the training process is to form a trained black box which can be used for data test. The data used in the training phase is data in subsection 3. 70% of the total data was used for this process.

Table 2 presents the statistical error value from five training methods with values from K-ELM having the smallest statistical error. This value indicates that in the training process, the output of K-ELM has the smallest gap with the measurement data. In sequential order, methods with the best statistical error value, following K-ELM, are SVM, ELM, LVQM BP and BR BP as presented in the following table.

Tabel 2. Statistic Error Comparison of Training Process

Forecast Method	Training		
	MAE	MSE	RMSE
K-ELM	0.112	0.029	0.171
ELM	1.705	6.555	2.560
SVM	0.254	0.100	0.316
LVQM BP	3.517	27.640	5.257
BR BP	3.240	21.583	4.646

Tabel 3. CPU Time for Training Process

Forecast Method	Training CPU Time
K-ELM	0.082 s
ELM	0.208 s
SVM	7.781 s
LVQM BP	6.391 s
BR BP	1484.3 s

Aside from presenting a comparison between statistical error values, the main objective in using K-ELM is to find the shortest CPU time. A short CPU time indicates that the method can perform the training process using the dataset in a rapid manner in real-time cases. The CPU time is needed by the power system operator to adjust the capacity of the power source from the solar panel. After generating the shortest CPU time through the training process, the network from K-ELM can be used for the testing process. As shown in table 3, CPU time of the K-ELM method is 0.082 second. Other methods with the closest CPU time are ELM with 0.208 second. With a difference of 60.56%, it indicates that K-ELM can perform the training process faster than ELM.

While for the three other training methods, the CPU time are much longer compared to K-ELM. SVM has a CPU time difference of 98.95%, while the NN LVQM method has a difference of 98.72% and the NN-BR method has a CPU time difference of up to 99.99%. A longer CPU time indicates that the method would require longer time to generate forecasting results.

Analysis and Performance Test

After completing the training process using 70% of the data set, this section further discusses the training process using the remaining 30% dataset. Similar to previous testing processes, data are normalized prior to the testing process. In this phase, K-ELM parameters previously obtained from the training process are simulated using the data test. Simulation results are further denormalized and converted using formula (1) and (2).

As seen in table 4, K-ELM has the smallest statistical error value, which is followed by ELM. The MAE value of K-ELM and ELM has a 76.5% difference, while their MSE value has a 95.47% difference and the RMSE value has a

97.87% difference. There is a big gap between the statistical error values of other methods, concluding that K-ELM is the leading method in obtaining a reliable forecast.

Tabel 4. Statistic Error Comparison of Testing Process

Forecast Method	Testing		
	MAE	MSE	RMSE
K-ELM	0.473	0.420	0.065
ELM	2.014	9.281	3.046
SVM	12.988	349.882	18.705
LVQM BP	3.372	22.653	4.760
BR BP	3.131	20.553	4.534

As seen on figure 4, the line representing forecast results of the K-ELM from data 300-320 is one that is closest to the measurement data. Moreover, if the graph is enhanced, it can be clearly seen how the output of K-ELM follows the trendline of the measurement data. The greater the statistical error value, the farther the line in figure 4 is from the measurement data trendline

Similar to the training process, the smallest CPU time is also required in the analysis and test performance. Simulation results of the CPU time is presented in table 5.

Tabel 5. CPU Time for Testing Process

Forecast Method	Testing CPU Time
K-ELM	0.065 s
ELM	0.960 s
SVM	0.203 s
LVQM BP	0.313 s
BR BP	0.172 s

As shown in table 4, the CPU time in each method used are considerately short, with a processing time of less than 1 second each. These results confirm that all methods proposed in this research can perform efficiently in a short amount of time in processing the PV output forecast using weather data. The table also shows a clear comparison of the testing time between the four methods. Result from the K-ELM method indicates that it can forecast the PV output in a very short amount of time, which is 0.065 s. This is 93.23% faster than the testing time of ELM, 67.98% faster than that of SVM 79.23% faster than that of LVQM BP and 62.21% faster than the testing time of the BR BP method.

In addition, K-ELM displays a better performance compared to the other methods. With the smallest statistical error value in the PV power output forecast, it is expected that K-ELM can be applied in other datasets.

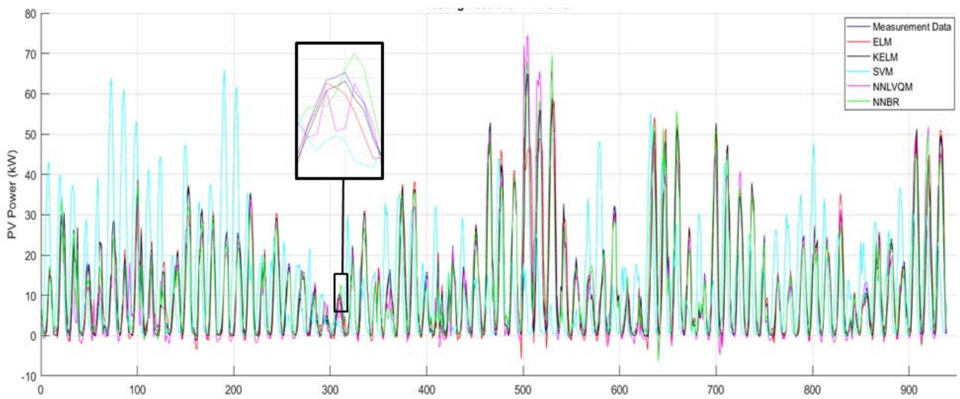

Fig. 4. Performance Test

Conclusion

This research proposes an advanced ELM in the PV power output forecast. The training method of kernel extreme learning machine (K-ELM) is simulated using historical dataset from January-March 2016 until 2019. To confirm the results, values from the K-ELM method were compared to values from other training methods such as ELM, SVM, LVQM BP, and BR BP. Based on the results, K-ELM presented the smallest statistical error value throughout the process. The proposed method also has a better CPU time compared to other methods, both in the training process and testing process. The CPU time of K-ELM is faster 0.895 second than ELM, 0.138 faster than SVM and so on.

While the proposed method shows promising results and values, more work is still required in order to optimize the accuracy of the output. Additional work to consider would include: (1) use of AI to optimize the parameters in the K-ELM method; (2) the use of a larger and more recent historical data in the training and testing process to generate the latest PV power output forecast; (3) application of a more advanced form of AI such as deep learning, grasshopper optimization algorithm, grey wolf optimization to get a better view on the comparison of PV output value and CPU time.

Nomenclature

Abbreviations:

ARMA	Auto Regressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
ANN	Artificial Neural Network
B-ANN	Bayesian Artificial Neural Network
BR BP	Bayesian Regularization Backpropagation
ELM	Extreme learning Machine
GTI	Global Tilted Irradiation
K-ELM	Kernel Extreme Learning Machine
LSTM-NN	Long Short-Term Memory Combined with Neural Network
LVQM BP	Levenberg Marquardt Back Propagation
MA	Moving Average
MAE	Mean Absolute Error
MSE	Mean Square Error
NWP	Numerical Weather Predictions
PV	Photovoltaic
RBF	Radial Basis Function
ReS	Renewable Energy Resources
RMSE	Root Mean Square Error
SLFN	Single Feedforward Network
SVM	Support Vector Machine
SARIMA	Seasonal Autoregressive Integrated Moving Average
A	PV size (m^2)
I	the PV size (m^2)
η_0	the conversion efficiency value (12,88)
γ	constant value for temperature coefficient, usually between 0.003/°C until 0.005/°C

β_i	weights value on the hidden layer and output layer
g_i	the number of output layer as data input x
$\hat{y}_{out}$	forecast result
H	hidden output
C	coefficient of regularization
T	the predicted output or target output

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