Forecasting of Power Output of 2-Axis Solar Tracked PV Systems using Ensemble Neural Network

Catur Hilman
Department of Engineering Physics
ITS
Surabaya, Indonesia
hilmanadritya@gmail.com

E. Tridianto[1], T.H. Ariwibowo[2]
Department of Power Plant Technology - PENS
Surabaya, Indonesia
{[1]erik, [2]teguh}@pens.ac.id

Budiman P.A. Rohman
Research Center for Electronics and Telecommunication - LIPI
Bandung, Indonesia
budi028@lipi.go.id

***Abstract*—Photovoltaic (PV) based power generation system has been considered massively as one of renewable energy resource. However, the performance of PV system is sensitively affected by many factors including the weather and solar irradiance. The hybrid system is taken for solving this system output uncertainty. For improving the power management performance such this hybrid systems, the forecasting of power output of PV system has been proposed in some previous research. The precision of this forecasting has to be considered for building a high performed power management system especially for remote area where the very small power output is very important. Therefore, this paper proposes a novel approach of forecasting of power output of PV systems using ensemble neural network with four base forecasters. The PV system used in this research is equipped with 2-axis automated tracking with maximum output 10Wp. As base forecasters of ensemble structure, this research employs the multi-layer perceptron network with two hidden layer. According to the research results, the proposed method provides high accuracy prediction. Moreover, this method outperforms the individual MLPN based forecaster commonly used in the forecasting research.**

Keywords—photovoltaic, power, forecasting, ensemble neural network, accuracy

I. Introduction

Photovoltaic (PV) system has taken massively attention as the most prospective renewable energy resources. The research and development of this technology have been increased significantly in these decades [1]. However, this power generation system has uncertainty power output because it is very sensitive to some aspects such as weather, solar irradiance and climate changes [2]. The forecasting of the output power of PV systems has been proposed for solving this uncertainty regarding for making the better power management, especially for large hybrid systems.

There are some researches conducted in order to build a highly accurate PV power output forecasting. In 2007, Yona et al proposed the implementation of neural network for predicting the PV power output using the meteorological data. They compare three types of neural network including feed-forward neural network, radial basis function neural network (RBFNN) and recurrent neural network (RNN) which the result shows the superiority of RNN as one day a head forecasting [2]. Then, in 2012, Shi et al developed the forecasting method of PV system power output based on both weather forecasting data and actual historical power output data. The algorithm implemented in this study is support vector machine [3]. Then, in same year, Su et al developed the PV power output prediction using Gaussian equation validated by the measured data of PV systems installed in Macau [4]. Li et al, in 2014, proposed the forecaster of PV system power output using ARMAX model implemented in grid connected PV systems. This study results show that the ARMAX model outperforms the ARIMA and RBFNN algorithm [5]. Yang et al proposed the forecasting method which consists of three stages including classification, training and forecasting. In the classification stage, they implement self organizing mapping and learning vector quantization algorithm, then in training stagethey use support vector regression and for last stage they implement the fuzzy logic [6]. Otherwise, Dolora et al, in 2015, proposed the short term forecasting of PV system power output using physical hybrid neural network [7].

Meanwhile, the ensemble structure of classifier has been considered as highly reliable and accurate model facing the variance of data.Moreover, the ensemble structure shows that it has better performance than the single neural network [8-10]. The research implementing the ensemble models are as follows. In 2004, the ensemble of various neural networks consisted of multi-layer perceptron network (MLPN), Elman recurrent neural network, RBFNN and Hopfield Model was proposed for building a robust weather forecasting [11]. Then, in 2012, the weighting on local learning and diversity in ensemble structure has been investigated[12]. In 2013, the ensemble with hierarchical fusion and ten-fold cross validation were proposed for digital mammogram classification. This proposed method had a significant improvement over the single neural network and ADABOOST algorithm [13]. Barrow and Crone proposed the use of cross-validation data splitting for model averaging and assessed different forms of cross-validation for creating model diversity [14]. The development of neural network ensemble optimized with particle swarm optimization integrated Fuzzy Type 1 and 2 for time series prediction was conducted [15].

This paper extends the previous research mentioned above in order to improve the accuracy and precision of forecasting of PV power output focusing on the PV systems equipped by 2-axis automated solar tracking. This investigated system will be far more challenging than the fixed PV systems studied in

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Figure 1. PV system with 2-axis solar tracker built [16]

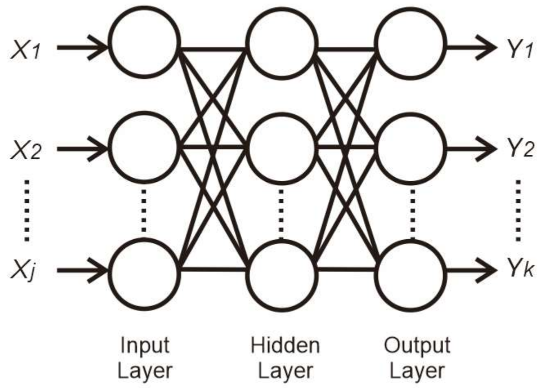

Figure 2. Common structure of MLPN

mostly previous research. That because instead of the weather and solar irradiance, the solar tracking employed on the systems will also affect significantly to the power output variance. This forecasting result can be a main reference for making the quick response on the power management of solar tracked PV systems especially if the system is integrated with the hybrid power generation scheme. The method proposed in this research is the ensemble structure of neural network with a variation of input and hidden neuron number. The neural network structure is selected to be employed as basis predictor in this proposed method besides of other artificial intelligent algorithms such as fuzzy logic or Bayesian classifiers since this method is able to classify/predict without any specific prior knowledge especially in the chaotic time series data.

The rest of this paper is organized as follows: section II describes 2-axis automated solar tracking PV systems and ensemble neural network. The methodology of this research is explained in section III. Results and discussion are given in section IV, followed by the conclusion of all conducted studies in section V.

II. Dual-Axis Solar Tracked PV Systems and Ensemble NeuralNetwork

A. Dual-Axis Automated Tracking PV Systems

The system employed in this research is PV system equipped with the 2-axis automated solar tracking system which has been developed and proposed in our previous research showed in Fig.1 [16]. As our experimental results, this system can result in power output up to 7.7 Watt in a certain period. This PV system consists of solar cell panel 10Wp, controller box and 2-axis mechanical parts as an actuator (See Fig.1). The solar tracking system uses the light dependent resistor and CMPS10 module sensor for tracking the solar position for achieving the highest generated electric power. The Fuzzy logic is employed in this system as the decision algorithm of the angle of PV depends on the solar direction and position including azimuth, elevation, and zenith angle. This system uses data acquisition systems to sampling the power output and other variables from the solar panel.

B. Ensemble Neural Network

The ensemble structure is model combining some base classifiers/models for minimizing the error of predicted/classified output.By employing this structure, the combined classifier/model can enhance the accuracy of output by taking the advantage the diversity result of each base classifier. Some combining methods can be taken such as averaging, weighted averaging and majority voting. The averaging method is very popular because of its simplicity and this research will use this method.

Then, in this study, the ensemble model is built by combining multiple neural networks with MLPN structure which is very popular for solving the very complex problem. The ensemble will take the output of each base neural network which then will be computed further to get a final result.

Figure 2 shows the illustration of MLPN.MLPN is a type of neural network which consists of some component such as input, weight, layer, neuron, output and activation function (See Fig.2). The layer is a set of neurons. A neuron is a place for multiplying the weight and input then running the activation function. The weight is the multiplier value of input in the neural network. Below is the mathematical equation of neural network,

$$v_k = \sum_{j=1}^{p} w_{kj} x_j \qquad (1)$$

where x_j is input, v_k is the summation of weighted input while y_k is the output of neurons.

III. Research Methodology

A. Data Preparation

For this preliminary study, we use two days data of output power in same weather season (3 and 7 June 2016) for both training and evaluation steps. The measurement was held in Surabaya, Indonesia with coordinate 7^{o}18’44.7804” S and 112^{o}42’53.5716” E in time range around between 07.30 WIB to 16.30 WIB, while the data number obtained, is around 6000 each day with sampling data 5 seconds. Before feeding to

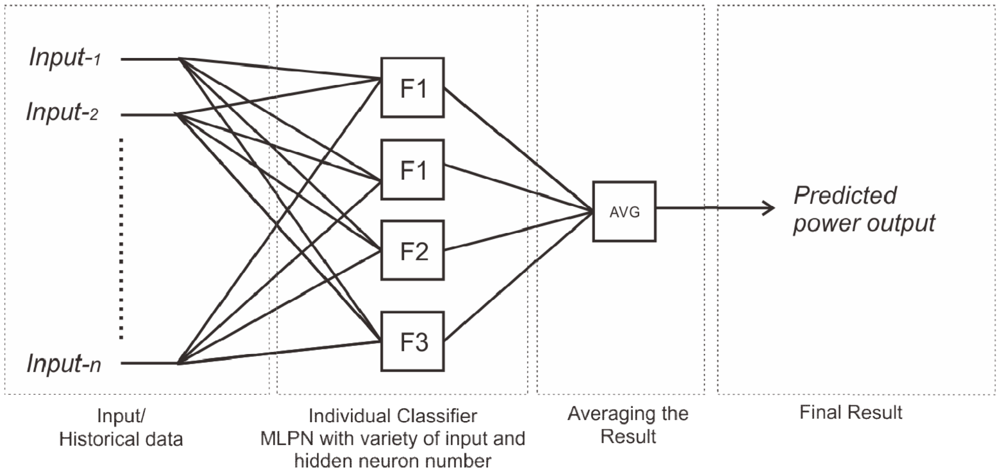

Figure 3. Ensemble Neural Network

the forecasting algorithm, the power output is preprocessed by normalizing it with the global maximum value of data.

B. *Proposed Ensemble Neural Network*

The proposed model of ensemble neural network in this study is shown in Fig.3. The structure consists of four base forecasters which the results of all base forecasters are then computed to take the average value. This value is then used as the final predicted result. In this scheme, the final forecasting result is five seconds ahead of PV power output in Watt.

The structure of base forecaster employed is MLPN with two hidden layers. The number of input is varied within 4, 6, 8 and 10 representing the historical data of power output of PV systems. Similar to the output of the ensemble model, the output of each base forecaster also represents the five seconds ahead of predicted PV power output in Watt. The hidden neuron number in the first layer is varied on each base forecaster depend on the number of input (such as 4 neuron when the input number is 4) while the hidden neuron number in the second layer is fixed as many as three neurons. The MLPN parameters used in all of the base forecasters are configured as follows; activation function: tan-sigmoid; learning rate: 0.5; maximum epoch: 5000; and learning method: Levendberg Marquadt. The trained of all base MLPNs build the ensemble structure which then will be tested and evaluated its performance.

IV. RESULTS AND DISCUSSION

After training each of base forecaster and testing the ensemble neural network built, the performance of the proposed method is calculated. Table 1 shows the comparison of mean-squared-error (MSE) result of the proposed method with its base of forecaster which the meaning of symbols are as follows, MLPN4: MLPN with 4 input; MLPN6: MLPN with 6 input; MLPN8: MLPN with 8 input and MLPN10: MLPN with 10 input. According to this result, it can be seen clearly that the ensemble structure is able to improve the performance of its base forecasters with single MLPN structures. The proposed ensemble neural network has lowest MSE within 0.0028 or error rate around 5.3%. In other words, the proposed ensemble structure can take the advantages of diversity of each basis MLPN model results.

TABLE I
COMPARISON OF MSE

Model	MLPN4	MLPN6	MLPN8	MLPN10	Ensemble NN
MSE	0.0034	0.0046	0.0036	0.0064	0.0028

Then, Fig. 4 shows the result of forecasting of the proposed method and the measured data in first 100 observed data. Generally speaking, the proposed method can predict accurately enough to the PV power output though some different values in some periods show up. For example, in range time 82 to 90, the method can predict the power almost perfectly. However, in time sampling around 94-97, the predicted data is higher than the measured data.

For investigating further about the advantage of ensemble structure to the single MLPNs, the comparison of predicted power was performed which result in Fig. 5 and Fig.6. According to this figure, the proposed method has the nearest result to the measured data among other models. Moreover, the MLPN-10 which uses 10 input historical data shows worst results. It means that the selected number of input data in general time series forecasting especially in this case will affect its performance significantly.

V. CONCLUSIONS

We have described the proposed ensemble neural network based forecasting method for the power output of PV system equipped with 2-axis automated solar tracker. The ensemble structure consists of 4 base models which is MLPN with varied input and hidden neuron number. For combining the results of base classifiers, we use the simple averaging method.

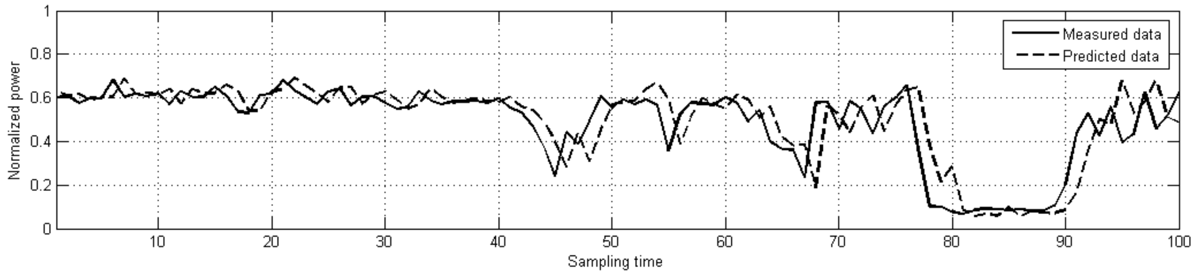

Figure 4. Result of prediction of proposed Ensemble Neural Network

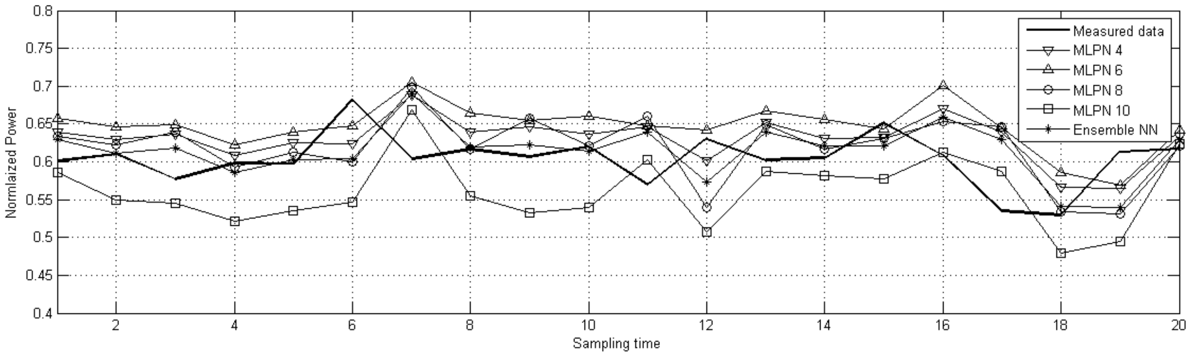

Figure 5. Comparison of proposed Ensemble Neural Network with single MLPNs

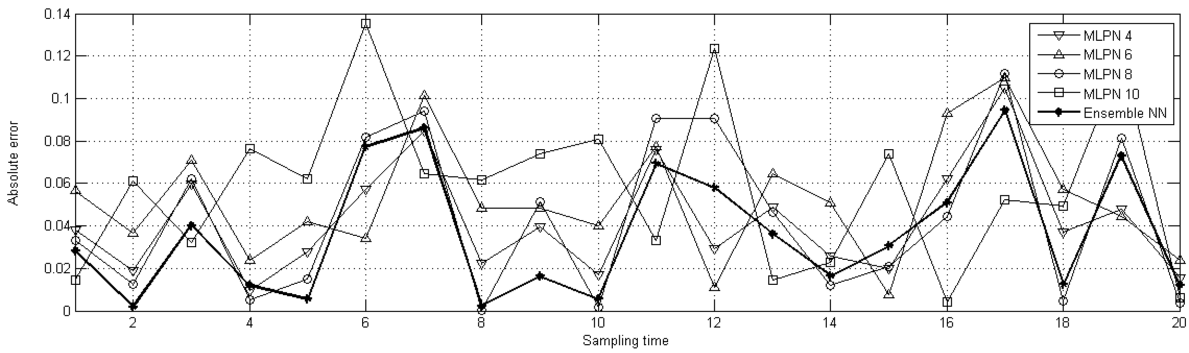

Figure 6. Comparison of error prediction of proposed Ensemble Neural Network and single MLPNs

According to the research results, it shows that the proposed method provides very accurate prediction with the MSE around 0.0028 or error rate around 5.4%.

For future works, we consider enlarging the both training and evaluation data in order to provide more comprehensive performance information. The variation of the period of forecasting are also considered for larger possible application of this forecasting scheme. Also, we plan to compare the proposed method with other existing methods in order to evaluate its computation time and accuracy.

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