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Photovoltaic (PV) Power Prediction Based on Artificial Neural Network with Activation Function Selection and Feature Reduction Method

Jordan Noche Velasco[1], Conrado F. Ostia Jr[2]

[1] Pamantasan ng Lungsod ng Valenzuela,[1] Mapua University Graduate School Student, [2]Mapua University School of EECE

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Abstract

This paper presents an extensive review of the ANN Based PV Power Output Prediction Model and the exploration of the effect of the common meteorological variables that is used in some research work. This study will discuss the result of the two simulated Models, wherein Model A uses all the parameter as the input variables and Model B applied the feature reduction method that explores all the possible reduced parameter combinations.

A data set consisting of 755 variables (PV power output model) were used to trained and test a 2- layer (1 hidden layer) neural network model. The study simulated two models A and B. The model A used the conventional method of modelling, training and testing using the six input variables such as solar irradiance (G), maximum temperature (Tmax), minimum temperature (Tmin), rainfall (Rf), wind speed (Ws), and relative humidity (Rh). After thorough simulation, the final neural network for model A with six input variables, with 8 hidden neurons, using tan sigmoid activation function, 1 layer and 1 output node. The coefficient value of the PV power model was R (All) = 0.89264, R(Test) = 0.89071, R(Training) = 0.88527, R(Validation) = 0.92738, MSE = 0.025118. For the final Model B, the best parameter combination is consisting of four variables the G, Tmax, Tmin and Rh with 10 hidden neurons, using tan sigmoid activation function, 1 layer and 1 output node. For model B, the results are R(All)= 0.9034, R(Test) = 0.87312, R(Training) = 0.8969, R(Validation) = 0.95613, MSE= 0.024645. Based on testing and validation of Model A and Model B, the MAPE are 44.06% and 19.88% respectively.

The study shows that the Model B using four input variables with solar irradiance, maximum and minimum temperature and relative humidity provides good forecasting results predicting solar pv power output, as justified by the result of its MAPE obtained from the validation and testing of data.

Index Terms: *Artificial Neural Network, Prediction Model, Solar PV System, Grid Connected PV System*

I. INTRODUCTION

Prediction of power output from the large- and small-scale Solar PV System plays a major role in the energy generation and management sector, however since the energy generated from this system varies from time to time and its stability and reliability depends on the weather climatic conditions. With the fluctuating behavior of the generated energy, the grid operators faced the challenges in controlling, monitoring and integrating it to the main power grid. Thus, an advanced information of the status as well as its generated energy will be very essential in the energy management scheme.

Numerous of research paper that focuses on PV power output prediction approaches have been

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studied and still under thorough development, one of this is the Multiple linear regression [1][2] which is used to study the behavior of solar power output, with the aid of various meteorological and solar irradiance data. However, this approach will be needing many datasets. The author in [3] developed an algorithm to predict pv power output based on different classification of weather and Support Vector Machines (SVM). The author classified the weather based on following conditions such as rainy day, clear sky, foggy and cloudy day. The model was created to predict pv power output one day ahead based on weather predicted data, and actual recorded power output data and the SVMs.

However, since Solar energy generation forecasting is a typical multi – classification cases SVM algorithm is not suitable for this application.

Many studies have been conducted to develop the methodologies in Solar PV Power Output Prediction using ANN. In [4] the author used two ANN models, the first generated Model is used to predict solar irradiance which will be one of the parameters of the second generated model, to predict voltage and current that will result to power output. Various research for solar PV output prediction techniques were done in the past. The paper presented in [5] discussed about prediction of PV panel output power using the minimum, maximum and mean temperature and solar irradiance which serves as their input variables in the ANN model, then they used a mathematical equation that will estimate the generated Power. The study of [6] developed a method that uses Pearson correlation coefficient to analyze the correlation between the weather data and the generated power and will decide base on the result which information is required to develop the ANN model, which only focuses on common activation function.

In the study of [8], a forecast model based on ANN where used to study the correlation of Irradiation and PV power output that will develop a next day power prediction model based on real time data, a three-layered feedforward neural networks were utilized. In [9] the researcher used three different types of ANN model, the data used was extracted from a weather station logging system. Based on this study the ANN model attained 95% accuracy for prediction. With this result, it shows that ANN is the most suitable prediction model as compared with other AI methods, it also shows that ANN has a much simple and less computational method.

Despite of numerous studies which focuses on Solar Power Output prediction, it still hard to identify the relevant input parameters necessary for the prediction methods. Therefore, there is a need to explore the effect of different combination of reduced parameters to somehow identify highly relevant parameters. This study will apply an ANN based Prediction model using different number of hidden neurons with different activation function present in MATLAB software. It will also present the best model considering the best parameter combination and discuss the difference in characteristics and performance of the two models with complete parameters (model A) and reduced parameters (Model B).

In this paper, the thorough exploration of different models with different reduced parameter combination and activation function will be evaluated based on the conventional prediction modelling and simulation. The feed forward back propagation will be utilized as its network topology for and the Levenberg - Marquard (LM) learning algorithm will be applied in the simulation. This study will benchmark the effect of different application of parameters and activation function in the target prediction model. This methodology would serve as reference for other research for potential assessment for the development and expansion of existing system. It may lead to less complicated data gathering since it will only need lesser variables. This study will also validate the impact of different meteorological variables to the Solar PV Power generation.

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II. METHODOLOGY

A. Data Collection

The framework presents the ideas and principles regarding the development of a Week Ahead Solar PV Power Output Models using the conventional approach of Artificial Neural Network (ANN) and with application of Parameter Reduction and Activation Function Selection. The input variables such as solar irradiance, rainfall, temperature (maximum and minimum), relative humidity, and wind speed were collected from the PAGASA - Climatology and Agro meteorology Department (CAD) and the Power Output is extracted from the existing PV monitoring system of a 77kWp Grid Connected PV System located at the roof top of the ALERT Center Building at Mc Arthur Highway, Brgy. Malinta, Valenzuela City (see Figure 2). ANN was used to create a model based on the evaluation between the model "A" which uses the six input variables and model "B" which was been subject for parameter reduction based on manual exploration of parameter different reduced combination. The framework of the study is shown in the figure 1.

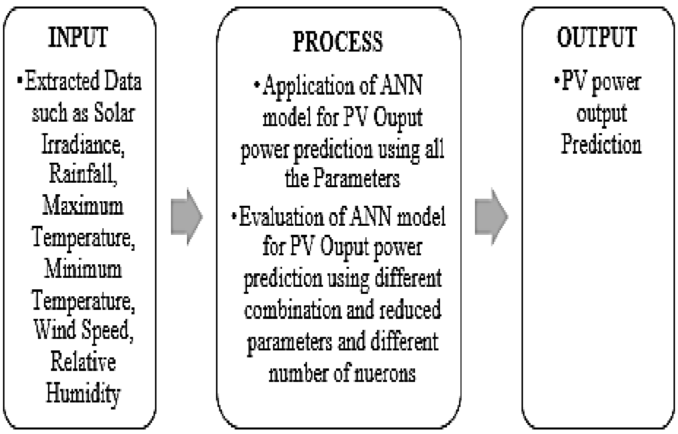

Figure 1: Conceptual Framework

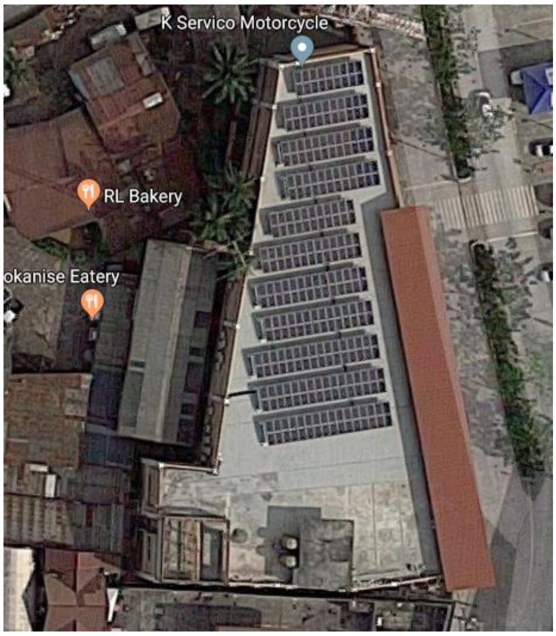

Figure 2: Top View of the Study Area (ALERT Center Building)

B. Model Development using Artificial Neural Network

In this study, simulation using linear transfer function (purelin), log sigmoid transfer function (logsig) and hyperbolic tangent function (tansig), and as the activation/transfer function was utilized. According to [10] Levenberg – Marquardt (LM) back propagation learning algorithm gave the best result when it comes to prediction, thus, in this study LM is used. Before the training phase takes place, the input and output data sets were normalized to range between -1 and +1 using equation 1.

$$y = \frac{(y_{max} - y_{min})(x - x_{min})}{(x_{max} - x_{min})} + y_{min} \tag{1}$$

Some papers used more hidden layers to handled complicated and erratic cases [11]. However, [12] recommend to used one or two hidden layer thus, this study uses one and two hidden layers. For the number of Hidden Nodes, the study of [13] discussed technique to calculate the number of hidden neurons. In this paper the author use 2 – 12 Hidden Neurons. After the series of simulation exploration, the performance of ANN Model will be

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evaluated using Correlation Coefficient (R Values) and Mean Square Error (MSE) which was obtained from MATLAB Simulations, the ANN model with the R values closer to one and MSE values near to zero will be the best model obtained. The values of R and MSE are used as the criteria of the training simulation in deriving the final weights and biases of the best model. Figure 3 shows the PV Power prediction model flow chart.

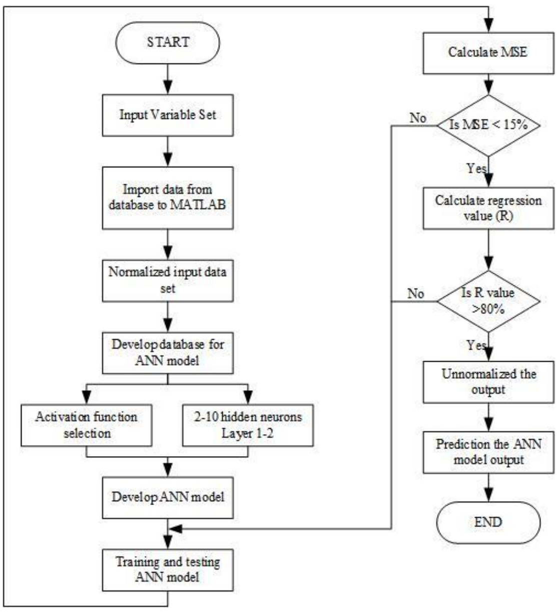

Fig. 3: PV Power Prediction Model Flow Chart

For the Model A, the model will use all the six (6) input variables obtained from the database using different number of hidden neurons and activation function such as tansig, logsig and purelin. Figure 4 shows the Model A Implementation step flowchart using the conventional simulation and using all the parameters.

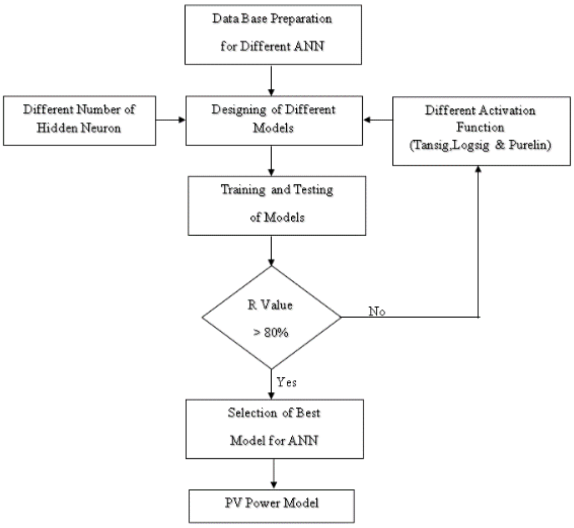

Figure 4 Model A Implementation Steps Flowchart

For the Model B, it will be simulated and explore all the possible combination of the input variables by reducing one and two variables utilizing the tansig, logsig and purelin activation function and different number of hidden neurons. Figure 5 shows the flowchart of the Model B simulation.

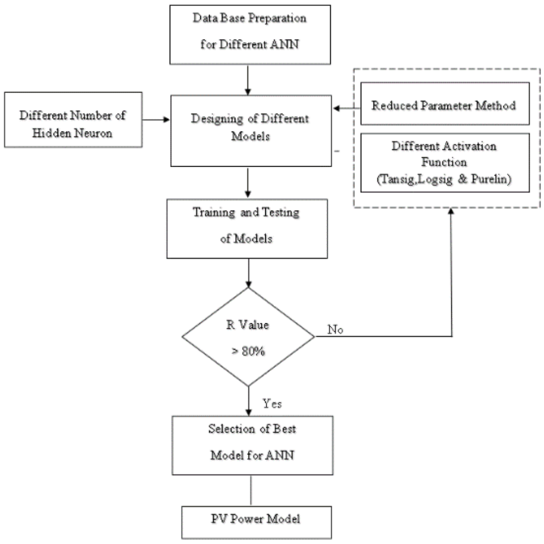

Figure 5: Model B Implementation Steps Flowchart

Figure 6 and 7 shows the architecture of model A with six (6) parameters and Model B with four (4) parameters using eight (8) neurons and ten (10) neurons respectively. The number of this neurons

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and input parameters are based on the manual exploration of different combination.

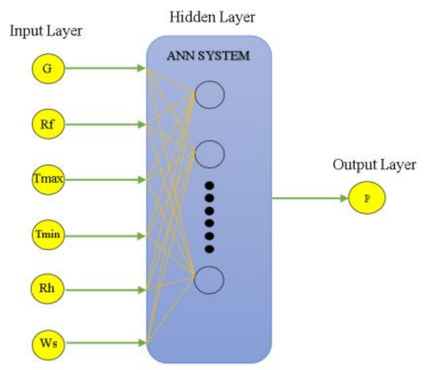

Figure 6: ANN PV Power Output Architecture Model A (6input-8hidden neurons)

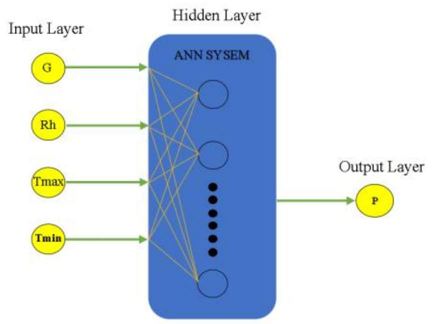

Figure 7: ANN PV Power Output Architecture Model B (4input-10hidden neurons)

D. Data Interpretation

The Artificial Neural Network (ANN) data set is divided into different phases, first is the training phase wherein the input variables will be trained using such iterations, next is the testing phase, where the input variables will be tested and finally the validation phase where the validation process takes place to obtained the best network configuration and training variables. The training set is the data provided to the ANN model for training the network. The objective is to find the model with the greatest validation test value closer to 1 and minimum mean square error value closer to zero. The Correlation of Coefficient (R)Values and MSE are used to compute the connection and the variance between calculated and predicted values. The formulas for computing MSE and R are as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - p_i)^2 \quad \textbf{(1)}$$

$$R = \frac{\sum_{i=1}^{n}(x_i - \bar{x}_i)(p_i - \bar{p}_i)}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x}_i)\sum_{i=1}^{n}(p_i - \bar{p}_i)^2}} \quad \textbf{(2)}$$

Where:

$x_i = targeted\ or\ real\ value$

$\bar{x}_i = mean\ of\ targeted\ or\ real$

$p_i = network\ output\ or\ predicted\ value$

$\bar{p}_i = mean\ of\ network\ output\ or\ predicted\ values$

$n = number\ of\ data\ sets$

The performance of the two models will be evaluated based on the validation phase resulted Mean Absolute Percentage Error (MAPE). The MAPE is given by equation 3, the best model is the model with minimum obtained MAPE.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|Actual(i) - Predicted(i)|}{Actual(i)} \times 100 \quad \textbf{(3)}$$

Two models (Model A and B) for pv power output will be the output models of the Neural Network. For each power output model, the ANN model with maximum goodness of fit (R) was selected. The models were based on the variables presented: solar irradiation, temperature (maximum and minimum) , relative humidity , wind speed and, and rainfall,. A model was generated and evaluated to represent the forecast of the pv power output. This model may be integrated and used by the Valenzuela City, ALERT Center to forecast the week ahead pv power output of its existing system considering the above-mentioned factors.

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III. RESULTS AND DISCUSSION

Results and Discussion

The purpose of this study was to derive an equation using the ANN generated weights and biases to predict the pv power output, and evaluate the effectiveness of the two models, Model A which uses all the parameters, and Model B with lesser parameters. A data set consisting of 755 variables (PV power output model) were used to trained and test a 2- layer (1 hidden layer) feedforward neural network model. The study simulated two models A and B. The model A used the conventional method of modelling, training and testing using the six input variables such as solar irradiance, wind speed, temperature (maximum and minimum), rainfall, and relative humidity). After thorough simulation, the final neural network for model A with six input variables, with 8 hidden neurons, using tan sigmoid activation function, 1 layer and 1 output node. The coefficient value of the PV power model was R (All) = 0.89264, R(Test) = 0.89071, R(Training) = 0.88527, R(Validation) = 0.92738, MSE = 0.025118. For the final Model B, the best parameter combination is consisting of four input variables; solar irradiance, Maximum and Minimum Temperature and Relative Humidity with 10 hidden neurons, using tan sigmoid activation function, 1 layer and 1 output node. For model B, the results are R(All)= 0.9034, R(Test) = 0.87312, R(Training) = 0.8969, R(Validation) = 0.95613, MSE= 0.024645. Based on testing and validation of Model A and Model B, the MAPE are 44.06% and 19.88% respectively. With this result obtained from this study, it shows that using lesser variables will make the prediction method simpler and fast with high percentage of accuracy. Figure 8 and 9 shows the result during the validation and testing of external inputs to predict the power for June 2019.

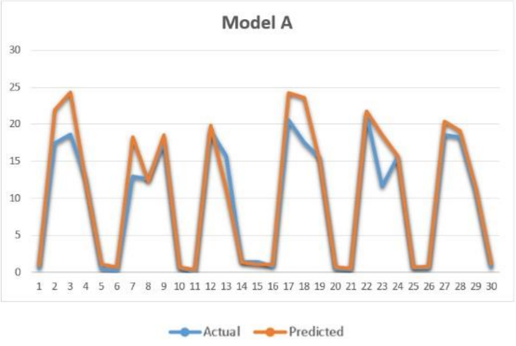

Figure 8: Actual vs. Predicted value for June 2019

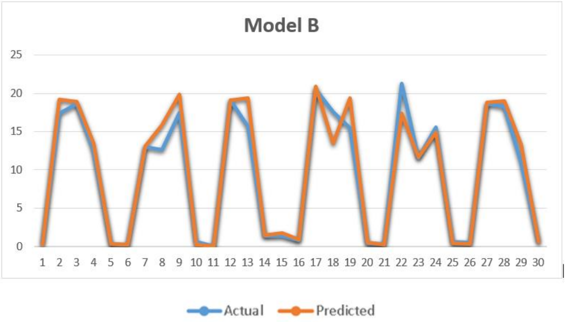

Figure 9: Actual vs. Predicted value for June 2019

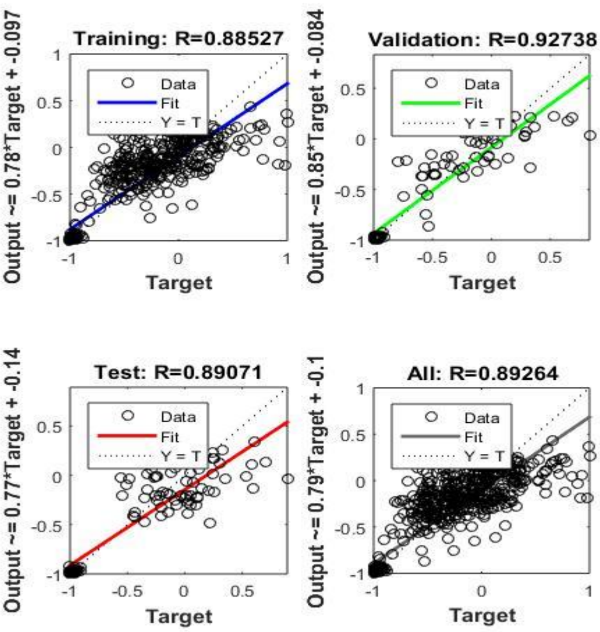

Figure 10: Regression Values for Model A

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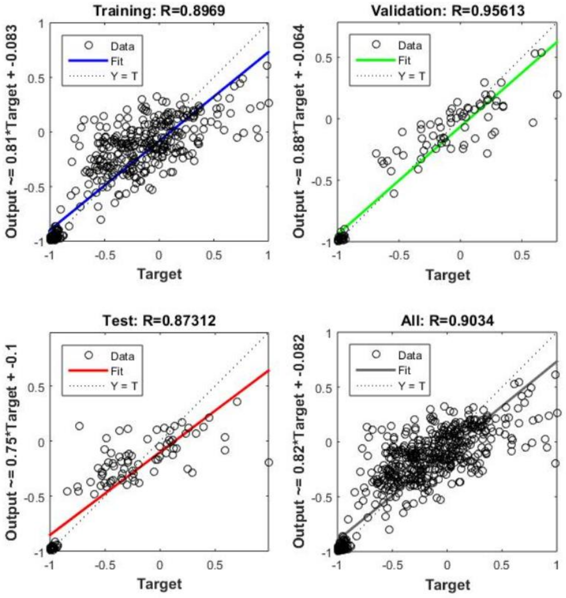

Figure 11: Regression Values for Model B

Based on the summary of simulation results shown on Table 1 for R Values, MSE, and the Computed Mean Absolute Percentage Error (MAPE). It shows that the reduced parameters compose of Solar Irradiance (G), Relative Humidity, Maximum (Tmax), and Minimum Temperature (Tmin) shows good prediction model.

Table 1. Summary of Results

Input Parameters	HN	R (ALL)	Test	Train	Validation	MSE	MAPE
Model A Irradiation Rainfall Tmax, Tmin Windspeed Relative Humidity	8	0.89264	0.89071	0.88527	0.92738	0.03511	44.06 %
Model B Irradiation Tmax, Tmin Relative Humidity	10	0.9034	0.87312	0.8969	0.95613	0.02464	19.88%

IV. CONCLUSION

This paper presents an exploration study to an ANN model by using different activation function, number of hidden layers and neurons in predicting PV power output. Its main objective is to conduct extensive evaluation of the common meteorological variables affecting the PV power generation of a roof mounted 77kW Grid Connected PV Power System located at ALERT Center Building of the City Government of Valenzuela. The study shows that the prediction model with lesser and relevant input parameters will have a high accuracy compared to models which uses many variables.

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