Deep Neural Network based on Genetic Algorithm and Ensemble Methods for Regional Solar Power Forecasting in Thailand

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***Abstract*—This article presents Deep Neural Network (DNN) based on Genetic Algorithms (GA) and Ensemble Methods for Regional Solar Power Forecasting in Thailand for one day in advance by using forecast weather data, real measured data and Solar power data and applying DNN with structure (window size, number of neurons in hidden layer, activation function, loss function, optimizer, numbers of epoch) designed with GA as well as using Ensemble Methods to blend the forecast values from each model together with Neural Network to improve predictive accuracy which is the solar power forecast. This article uses a total of 7 power plants with total power generation capacity of 436 MW. The strength of the proposed method is 1) Using inputs from multiple models to improve accuracy. 2) Weights are provided for weather forecast station surrounding power plants. 3) Models are structurally designed with GA. 4) Combining the advantages and decreasing the disadvantages of other models, by applying all these techniques for forecasting the total power generation capacity of all 7 solar power plants as a case study and found that the Root Mean Square Error was 5.61%, which decreased by 1.71% compared to the single model that provides the best forecasting results.**

Keywords—Neural Network, Genetic Algorithm, Ensemble Methods, Weather forecast, Solar power forecast

I. INTRODUCTION

The power generation from solar power plants that are fed to the grid system of Thailand is likely to increase every year. The challenge is to plan this energy management together with other types of energy in the system. Each type of energy has a different time to take from start until ready to supply energy (start-up time) and electrical energy from solar energy fluctuates depending on the weather. Therefore, if there is no solar power forecasting system, we must consider increasing the reserve capacity; Spinning Reserve (The electric power which is reserved to prevent the power plant from disconnected from the system immediately) in order to accommodate the highest fluctuations which increase every year. Increasing the spinning reserve will increase the overall electricity cost. But in fact, the fluctuation of the power plant doesn't reach the highest point all the time. So, adjusting the Spinning Reserve to the highest level at all times will cause the opportunity loss in cost during the fluctuation of the power plant which is not at the highest level according to statistics. Therefore, in order to reduce such costs, having a solar power forecasting system with both long-term accuracy (weekly), medium-term (1 day in advance) and short-term (every 15 minutes to 3 hours) will help support the work of National Control Center (NCC) to manage Spinning Reserve appropriately according to time and real fluctuation level in electrical systems.

There are methods to forecast the power generation capacity of solar power plants presented in a variety of researches [1-3]. In most cases, forecasting methods are based mainly on time frames of forecasting. For short-term forecasting, the inputs used will be the amount of cloud and cloud direction in the vicinity of the forecast area. In the medium-term forecasting, the inputs used will be weather data in that area, such as temperature, humidity, irradiance intensity, wind speed, wind direction, etc. And in long-term forecasting, the inputs used will be weather forecast data from numerical weather prediction [4]. Thus, the forecasting in this presentation will use weather forecast data from various weather forecast models and weather data from measuring devices. Weather forecast models or forecasting methods which are presented in a variety of researches have different advantages and disadvantages. For this reason, the researcher applied the Ensemble Methods to blend the forecast values from each model by using Neural Networks to find the appropriate weights for each model. The Deep Neural Network model used in the forecasting has also been designed to suit the region with Genetic Algorithm to improve the accuracy of prediction.

This article presents Deep Neural Network based on Genetic Algorithm and Ensemble Methods for Regional Solar Power Forecasting in Thailand for one day in advance, by applying various techniques including 1) Using inputs from many models to add weather data that is related to forecasting for the model. 2) Using Genetic Algorithm to appropriately design the structure of the model to increase the accuracy of prediction. 3) Using the Ensemble Methods to blend the forecast data from each model together with the appropriate weights, by applying Neural Networks to determine such weights in order to obtain high accuracy predictive results.

II. FORECASTING PROCEDURES WITH THE PROPOSED METHOD

A. Forecast Overview

The forecast is divided into 4 steps as shown in Figure 1 which shows the steps of the proposed method. Details of each step are as follows; 1) Data cleaning process to check and correct or delete incorrect data from training data such as

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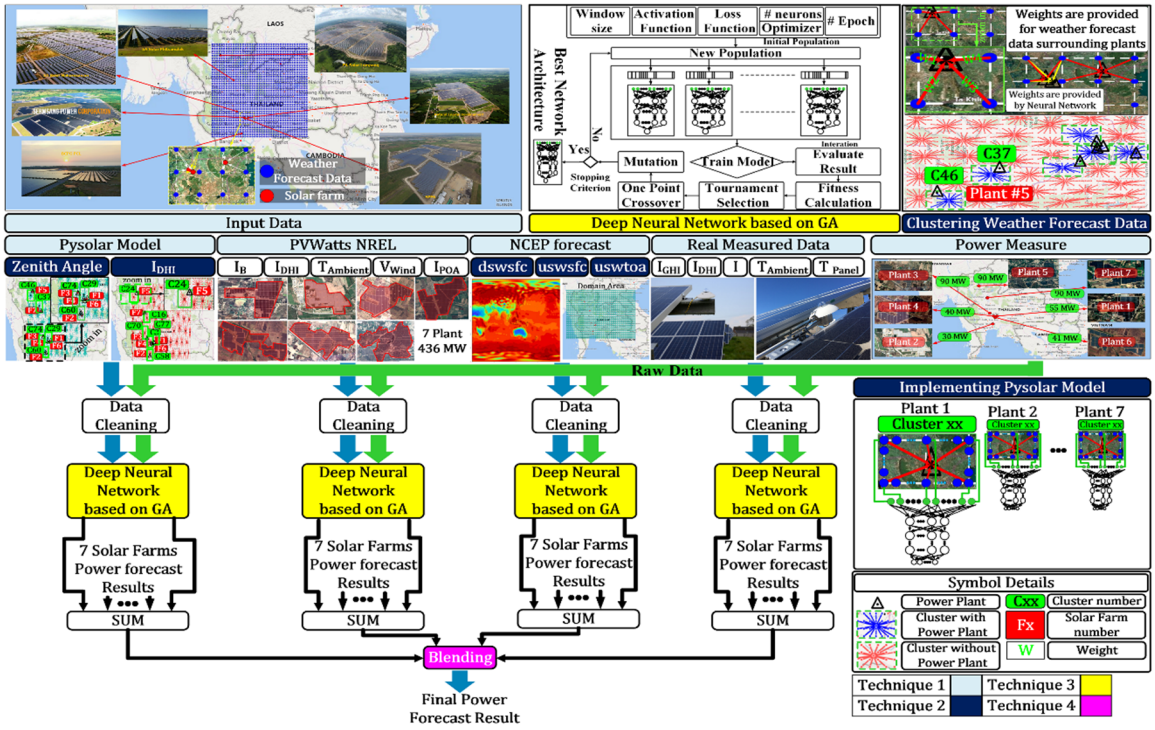

Fig. 1. Overview of the proposed forecasting method for the power generation of solar power plants

missing values. 2) Train model by using Neural Network which is structurally designed based on Genetic Algorithm for all 7 solar power plants. 3) Gathering forecast results from all 7 power plants. 4) Blending the predictive values from the previous step together using Ensemble Methods with Neural Network to obtain the final forecasting results.

B. Design Deep Neural Network based on GA

There are 5 steps of Genetic algorithm: 1) Initialization which is the process of creating chromosomes that have different characteristics. 2) Fitness Calculation. 3) Chromosomes Selection by using the Tournament Selection method. As the research [5], compared the selection method performance between the Tournament Selection and the Roulette Wheel Selection and found that the Tournament Selection has better performance because it allows the Genetic Algorithm to achieve solutions (converge) faster. 4) Crossover by using One Point Crossover method. 5) Mutation; the whole process is repeated until the stopping criterion is obtained.

In general, the structure of the neural network is designed through trial and error, which takes a long time to get the proper structure. Nowadays, computers have much higher computing capacity, resulting in Reinforcement Learning and Evolutionary Algorithms being more widely used to automatically find the appropriate parameters. The research has applied Genetic Algorithm to find the number of hidden layers and the weights connected between neurons. In this article, Genetic Algorithm is applied to find the appropriate structure of the model (window size, number of neurons in the hidden layer, activation functions, loss function, optimizer, number of epoch) The structure of the Neural Network obtained from Genetic Algorithm is shown in Table I below

C. Ensemble Method Using Neural Network

In this article the Ensemble Method is applied to blend forecasting results from each model together as shown in Figure 2 to improve forecasting accuracy.

TABLE I. STRUCTURE OF NEURAL NETWORK FROM GA

Parameters	RNN with GA	RNN without GA
Window size	32	8
Number of neurons	278-303-142	512-512-512
Activation Function	Relu-Relu-Relu	Relu-Relu-Relu
Loss Function	MAE	MSE
Optimizer	Adam	RMSprop
Number of Epochs	27	30

Each input model has a prediction advantage in different scales. Some models can predict well in short-time frame, such as 15 minutes to 3 hours. Some models can predict well in 1-day time frame, etc. This article, therefore, has applied Neural Network to determine the appropriate weights for forecast data from each model to get the final forecast data that is accurate in every forecast time frame.

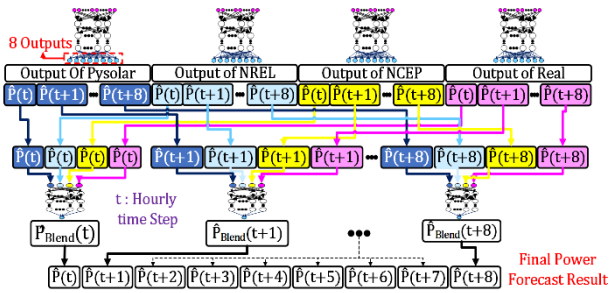

Fig. 2. The ensemble method using neural network

D. Recurrent Neural Network Model

Recurrent neural network is suitable for time series data because there are internal hidden layers for storing status information according to the equation (1) - (2),

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$$h_t = \sigma(x_t W + h_{t-1} U) \quad (1)$$

$$o_t = \sigma(h_t V) \quad (2)$$

where h_t is the state at the time t, x_t is the input vector, o_t is the output vector, σ is the activation function, and $U, V, and\ W$ is the weights matrix. Since the Recurrent Neural Network is suitable for the time series which time sequence is not very large; if it is, it will cause Vanishing Gradient. In order to solve this problem, a long short-term memory (LSTM) type of Recurrent Neural Network was developed using hidden state and cell state for data storage and processing in the next period. The gate will evaluate how much data should be stored in hidden state and cell state. The LSTM consists of input gate, output gate, and forget gate. each gate decides whether data should be allowed to pass or not. That is, it will be told when the data should be written, forgotten, or allowed to read by considering the importance of data. The data that has very little value will not be able to pass through the gate, which will help reduce the Vanishing Gradient which has equations according to (3) - (6),

$$i_t = \sigma(x_t W_i + h_{t-1} U_i) \quad (3)$$

$$f_t = \sigma\left(x_t W_f + h_{t-1} U_f\right) \quad (4)$$

$$o_t = \sigma(x_t W_o + h_{t-1} U_o) \quad (5)$$

$$c_t = (c_{t-1} \circ f) + \left(i \circ \sigma(x_t W_c + h_{t-1} U_c)\right) \quad (6)$$

$$h_t = \sigma(c_t) \circ o \quad (7)$$

where i is input gate, f is forget gate, o is output gate, c is the cell state, h_t is the state at the time t, σ is the activation function, U and W are weights matrix.

III. Data Description

The data used in the forecasting consists of 3 types, namely, the power generation capacity from the solar power plants, weather forecast data and weather data measured from measuring devices. Measured power generation capacity data of all 7 solar power plants in Thailand can be downloaded from the Renewable Plant Data Database of the Energy Regulatory Commission (ERC), which is hourly data. For weather forecasts that correspond to the location of each solar power plant, the researchers used three free weather models, namely Pysolar, PVWatts, and NCEP Forecast. All three models provide various variables, as shown in Table II, which are Altitude degree (θ_Z), Solar irradiance on a PV panel in the Plane of Array (POA), Diffuse Horizontal Irradiance (DHI), Global Horizontal Irradiance (GHI), ambient temperature at the array height ($T_{Ambient}$), Back Panel Temperature ($T_{BackPanel}$), downward shortwave radiation at the surface (dswsfc), upward shortwave radiation at the surface (uswsfc), and upward shortwave radiation at the top of the atmosphere (uswtoa). Pysolar is a python language library that provides solar irradiance, azimuth angle, and altitude angle of the sun in every location on earth. PVWatts Platform is a platform developed by the US Department of Energy's National Renewable Energy Laboratory (NREL) that provides solar irradiance in the solar power plant area according to latitude and longitude identified. NCEP forecast, the final model, which was developed by National Centers for Environmental Prediction (NCEP), is a model that provides weather forecasts 4 times a day at 0000, 0600, 1200, and 1800 UTC. This model has 4 resolutions to select from, that is 0.2, 0.5, 1.0, and 2.5 Degree Horizontal Resolutions by providing forecast values every hour. [6] The measured data (The actual measurement data from the equipment in the each solar power plant) in various variables are listed in Table II.

IV. Experiments

A. K-means Clustering

Pysolar and NCEP input models provide predictive results in the form of grid point with reference to latitude and longitude positions. To improve predictive accuracy, this article would not only use the point that provides the weather forecast for the location of the power plant but also use the points around the power plant that has similar climate by

TABLE II. The Variables Which Are Used In 4 Input Models

Model	Variables
Pysolar	θ_Z, DHI
PVWatts	$POA,\ DHI, T_{BackPanel}, T_{Ambient}$
NCEP	$dswsfc, uswsfc, uswtoa$
Measure	$DHI,\ GHI,\ POA, T_{Ambient}, T_{BackPanel}, MW$

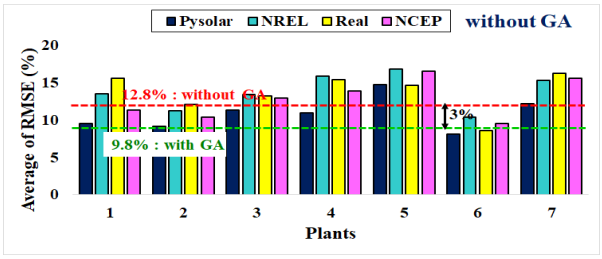

Fig. 3. The efficiency of the propsed method (without GA) for all 7 plants.

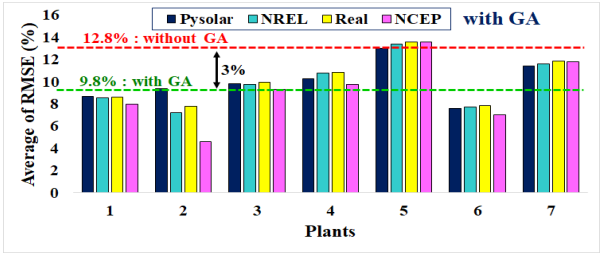

Fig. 4. The efficiency of the propsed method (with GA) for all 7 plants.

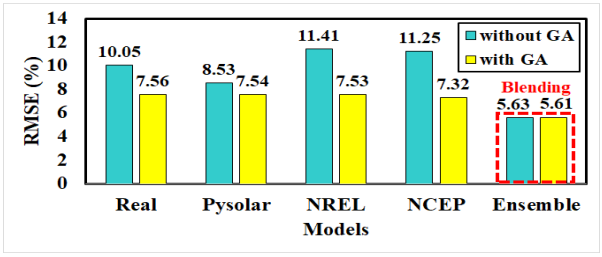

Fig. 5. The efficiency offered by various types of models.

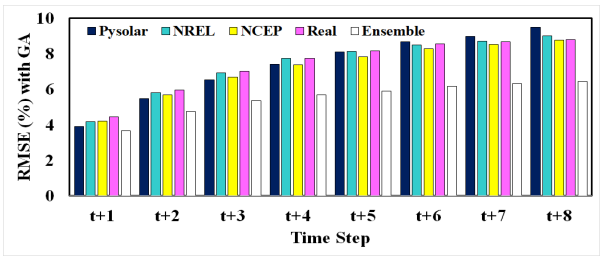

Fig. 6. The RMSE of each model in each time step

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applying K-Means Clustering techniques, divided into 78 groups, and used Neural Networks to give weights to each point or member in that cluster.

B. Evaluation Process

This article evaluated on the data from January 1, 2017 to December 31, 2017, divided into the training data (70%), the validation data (20%), and the testing data (10%). The index used in the evaluation is the Root Mean Square Error (RMSE) percentage of the solar power plant installed capacity. $RMSE = 100\% \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(\hat{P}(t) - \hat{P}(t)\right)^2} / (Installed.Cap.)$ RMSE percentage of each input model in each power plant is shown Figure 3 (without GA) and 3 (with GA) From blending the forecasting results of each model together, it was found that the accuracy of the forecast results from the proposed method has improved as shown in Figure 5, and Figure 6 shows the RMSE percentage in each time-step.

Parameter Setup: Epochs = 100 (performance testing : 5 times in each power plant), Loss function = Mean Absolute Error (MAE), Optimizer = Adam (learning rate = 0.0001), Reduce learning rate (validation loss, 10 patience, 0.1), Early Stopping (validation loss, 30 patience), Best epoch is selected in order to prevent overfitting. The efficiency of each power plant (loss function: MAE) in each model is shown in Figure 7 to 10. Figure 7-10 show that each model has low variances. The actual value compared to the forecast value of each model as shown in Figure 11.

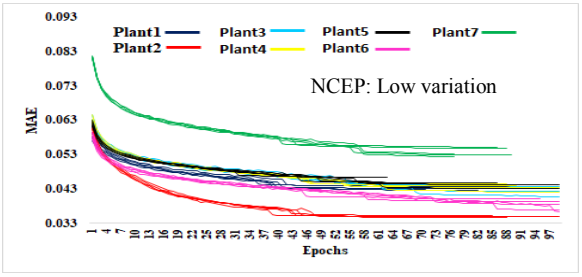

Fig. 7. The efficiency of the NCEP model in each plant with GA.

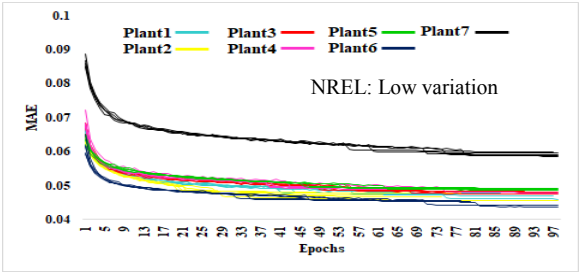

Fig. 8. The efficiency of the NREL model in each plant with GA.

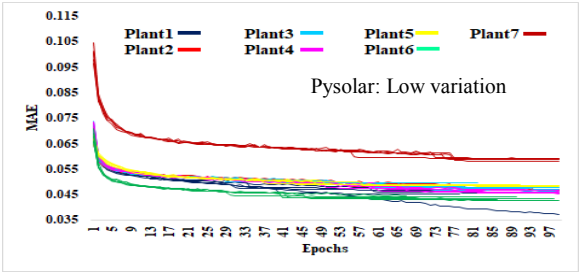

Fig. 9. The efficiency of the Pysolar model in each plant with GA.

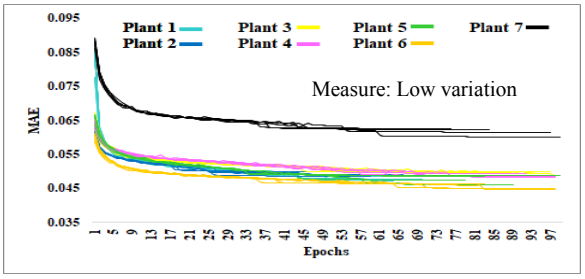

Fig. 10. The efficiency of the measure models in each plant with GA.

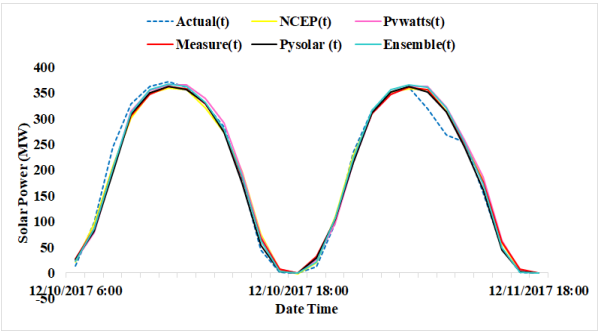

Fig. 11. The actual value compared to the forecast value of each model.

V. Results and Conclusions

This article presents Deep Neural Network with Genetic Algorithm and Ensemble Methods for forecasting the power generation capacity of solar power plants in Thailand for one day in advance that consists of 1) Use inputs from multiple models to improve accuracy. 2) Provide weights to the forecasting points around the power plants with K-Means Clustering and Neural Network. 3) Models are structurally designed with Genetic Algorithm. 4) Blending the advantages and disadvantages of other models with Ensemble Methods. From the case studies of the power generation forecast of all 7 solar power plants in Thailand, the proposed method gives the RMSE of 5.61%, which is reduced by 1.71% compared to the single model that provides the best forecasting results and has the low variation and medium bias.

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