

Assessment and prediction of daily average solar radiation In Chonburi with Neural Network Model

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Measurements of versatile variables; maximum temperature, minimum temperature, sunshine duration, sea-level pressure, relative humidity, pressure and solar radiation, at Chonburi during 2005 to 2009 were used to assess and build the neural network model for predicting daily average solar radiation. The study results revealed solar radiation and average solar radiation were highest in summer (mid February to mid May) successively in rainy season (mid May to mid October) and winter (mid October to mid February). The days of solar radiation potential were formed into 3 groups by cluster analysis. Cluster 1 represented roughly 6 hours for sunshine duration, 35°C for maximum temperature, 1006 Pa for sea-level pressure and below 70% for relative humidity. Cluster 2 illustrated sunshine duration fluctuated 7 to 11 hours, maximum temperature ranged from 34°C to 37°C, 1007 Pa for sea-level pressure and approximately 70% for relative humidity. Cluster 3 expressed roughly 10 hours for sunshine duration, maximum temperature proximately 33°C, 1008 Pa for sea-level pressure and above 70% for relative humidity.

[**Keywords:** Solar Radiation, Cluster Analysis, Neural Network Model]

Introduction

Approximately 50.2 %of Thailand gain the daily average solar radiation, varied 18-19 mj/m^2 . The report from solar monitoring stations which are distributed in every part notified the daily average solar radiation of Thailand in the unit of mj/m^2 was equal to 17.451². Therefore, most parts of Thailand have an opportunity for utilizing solar radiation all over the year. Chonburi is the eastern province having the limited solar monitoring stations. Moreover, the tool for measuring solar radiation called Pyranometer is still presently expensive and difficult for practitioner. Different techniques were applied for appraisalment or forecast the solar radiation; for example, correlation^{3,4,5,6,7}, coefficient of determination^{8,9}, regression model^{5,7,10,11}, neural network model¹², Angström, Bristow–Campbell and Allen models^{8,9,11}. To reduce the cost and difficulty for using Pyranometer, the neural network model was then chosen in this study as the alternative tool for predicting the solar radiation in Chonburi.

Materials and Methods

Seven variables were gathered and gauged from the Atmospheric Ozone and Solar Radiation Monitoring, Meteorological Observations Bureau,

Thai Meteorological Department since 2005 to 2009. Solar radiation (SR) was considered as the dependent variable. The other six remaining variables, maximum temperature (MaxTemp), minimum temperature (MinTemp), sunshine duration (SD), sea-level pressure (SLP), relative humidity (RH) and pressure, were the independent variables. Three steps of data analysis were as follows.

To determine the Chonburi's solar radiation pattern, the daily average solar radiation was assessed with descriptive statistic and cluster analysis. To predict the daily average solar radiation in Chonburi, both of neural network models, MLP and RBF, were trained and validated with the two separated observational data sets. The training data set approximately contained 7% of the whole data (705 cases) which were randomly selected. The remainder (303 cases) was the validation data set which was employed for investigating of model performance. All architectures of neural network model were composed of 3 layers; input, hidden and output. Two structures of input nodes in a layer were displayed. One was based on total 6 independent variables. The other was figured only by the influential independent variables correlated with the solar radiation. The appropriate number of nodes in a hidden layer was 3 and 5 nodes

regarding to the problem of undertraining and overtraining in accordance with13,14,15. The only one output node acted for solar radiation. The activation functions at the hidden nodes of MLP and RBF were successively hyperbolic tangent and Gaussian functions while exponential and identity functions were consecutively devoted at the output node.

To evaluate how competently the performance of predicted neural network model, root mean square error, RMSE, was one of the popular criteria to be chosen .It is formulated as of following Equation.

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

where y_i be the i th observation of solar radiation, $\hat{y}_i$ be the i th predicted value of solar radiation from derived model and n be the number of observations in the validation data set .Whichever model showed the smallest RMSE of validation data set, that model was assessed to be the best performance.

Results

The pattern of solar radiation in Chonburi could be described as of Figure 1. It displayed the solar radiation and average solar radiation were highest in summer (mid February to mid May) successively in rainy season (mid May to mid October) and winter (mid October to mid February). It also found the

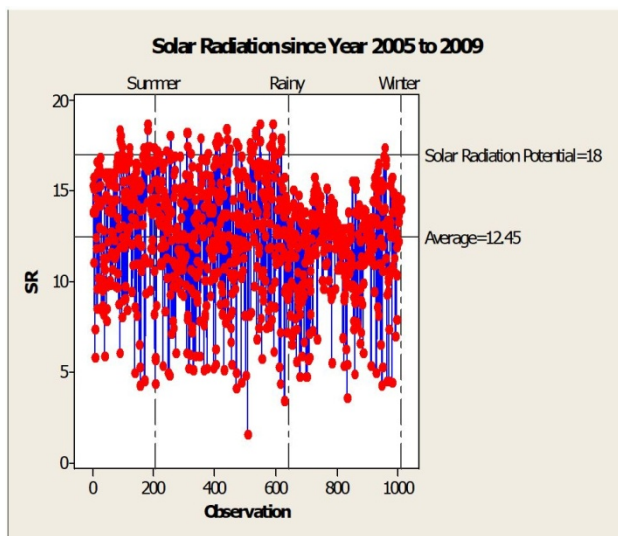


Fig. 1 — The solar radiation pattern in Chonburi

average solar radiation per year in the unit of mj/m2/day was 12.45. Solar radiation potential was then given as 18 because roughly 50% of Thailand received the annual average solar radiation ranged 18-19 mj/m2/day1. Only 16 days were thus analyzed and grouped by cluster analysis. Dendrogram of figure 2 classified the days of solar radiation potential into three different clusters; Cluster 1: roughly 6 hours for sunshine duration, 35C for maximum temperature, 1006 Pa for sea-level pressure and below 70% for relative humidity, Cluster 2: 7-11 hours for sunshine duration, 34°C-37°C for maximum temperature, 1007 Pa for sea-level pressure and approximately 70% for relative humidity, Cluster 3: roughly 10 hours for sunshine duration, proximately 33°C for maximum temperature, 1008 Pa for sea-level pressure and above 70% for relative humidity.

The p-value of Pearson correlation coefficient tests between the solar radiation and each of 4 independent variables (MaxTemp, SD, SLP and RH) were too small (<0.05). It led to conclude that all these 4 significant variables were affected to the solar radiation. Eight architectures of neural network model were then trained for predicting the solar radiation. The first four models, MLP6-3-1, RBF6-3-1, MLP6-5-1 and RBF6-5-1, consisted of total 6 independent variables for the input nodes as of Figure 3 and Figure 4. Last four models, MLP4-3-1, RBF4-3-1, MLP4-5-1 and RBF4-5-1, based on only the 4 influential variables for the input nodes as of Figure 5 and Figure 6.

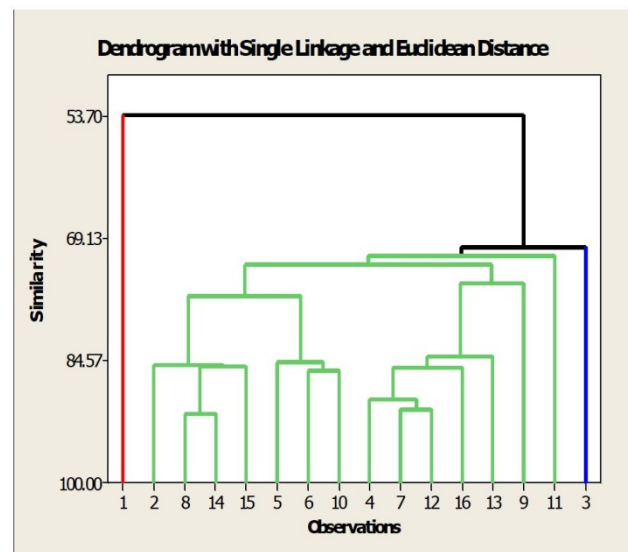


Fig. 2 —Dendrogram of solar radiation potential

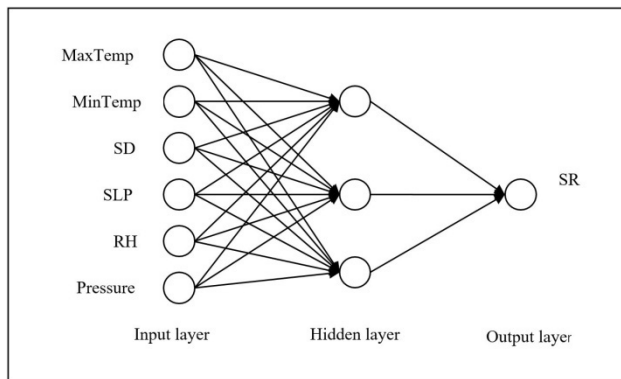


Fig. 3 — MLP6-3-1 and RBF6-3-1

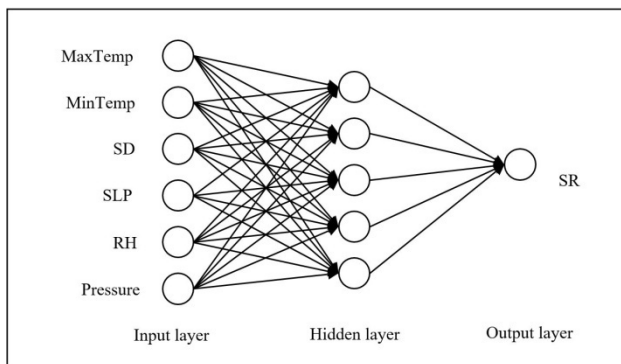


Fig. 4 — MLP6-5-1 and RBF6-5-1

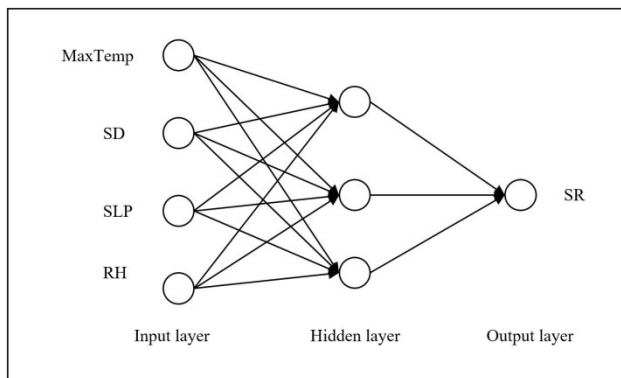


Fig. 5 — MLP4-3-1 and RBF4-3-1

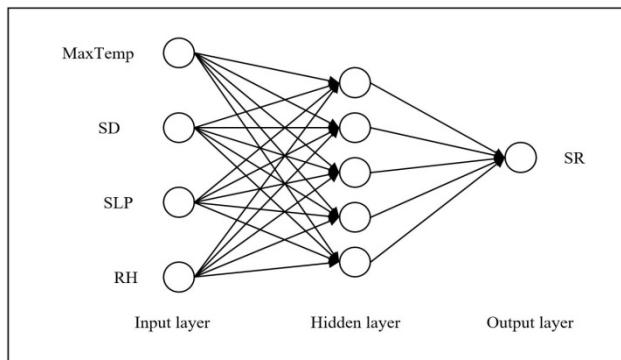


Fig. 6 — MLP4-5-1 and RBF4-5-1

Table 1 — RMSE for each of neural network model

Architecture of Neural network model	Activation function at		RMSE of	
	Hidden layer	Output layer	Training set	Validation set
MLP6-3-1	Hyperbolic Tangent	Exponential	2.194618	2.126665
MLP6-5-1	Hyperbolic Tangent	Exponential	2.128258	2.064196
RBF6-3-1	Gaussian	Identity	2.236302	2.118774
RBF6-5-1	Gaussian	Identity	2.215500	2.086546
MLP4-3-1	Hyperbolic Tangent	Exponential	2.302478	2.134538
MLP4-5-1	Hyperbolic Tangent	Exponential	2.420230	2.132204
RBF4-3-1	Gaussian	Identity	2.262867	2.172668
RBF4-5-1	Gaussian	Identity	2.363039	2.151030

To compare the performance of all neural network models, the RMSE of each of model was calculated as displayed in following Table.

Discussion

This study could be concluded and discussed as follows. Regarding to the test of Pearson correlation coefficient, there were four significant variables influenced to the daily average solar radiation in Chonburi; maximum temperature, sunshine duration, sea-level pressure and relative humidity. It was the same results in accordance with 3,8. Only using the simple neural network model was capable to precisely predict the daily average solar radiation in Chonburi as considering from the smallest RMSE of MLP6-5-1. Generally, the models with comprising network architecture of 5 hidden nodes furnished the small value of RMSE for the validation data set. Guideline for identifying the best neural network model for predicting in the daily average solar radiation are counting on the number of hidden layers, the number of hidden layer nodes even though the activation function at the hidden nodes or the output node.

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