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Research Article

ANN-BASED MODEL WITH ADAPTIVE OBSERVATION SYSTEM FOR ESTIMATION SOLAR IRRADIANCE AND ILLUMINANCE ON HORIZONTAL SURFACE

S. Hongkong*
Intelligent Artificial and Innovation Research Unit, Mechanical engineering, Faculty of industrial and technology, Rajamangala University of Technology Isan Sakonnakhon Campus, Sakonnakhon 47160, Thailand

ABSTRACT:
Continuous prediction of solar energy for designing has important. This article presented an estimation solar irradiance and illuminance on a horizontal surface by using artificial neural network (ANN) with the adaptive observation system (AOS). The AOS was detection system of inputs available for predicting, which consist of sky ratio and solar altitude angle. The sky ratio (SR) was using electronic circuit for detection. The solar altitude angle (α) calculate from sun position at latitude and longitude of a location with solar time. The 2-inputs (SR, α) and 4-outputs (Eeg, Eed, Evg, Evd) of solar irradiance and illuminance had been trained in ANN model. The feed-forward neural network with the back-propagation (BP) training algorithm was used train the model with 10 neurons, one hidden layer. The result shown comparison between estimation and measured by use MBD, RMSD and R^2*. The AOS is a novel technique for predicting and can be predicted solar quality whit out expensive instrument.*

Keywords: *All skies condition, Expert system, Artificial Neural Network*

1. INTRODUCTION

Solar radiation and daylighting were important for the functioning of all activities. The designing of energy system has to know the solar irradiance data, such as solar collector, photovoltaic or drying, etc., and solar illuminance for building design. The measuring cannot cover all areas because of the instruments is expensive. An estimation by using mathematical modeling has important, both solar irradiance and solar illuminance, which many researchers had been presented the modeling for estimating solar energy is always.

Linear or nonlinear modeling for predicting had been presented pass basic model. See in Angstrom model [1] has basic for predicting solar radiation, this model can use to calculate the global solar energy in terms of the sunshine hours, daily or monthly. However, the Angstrom model has been developed for predicting of another model.

Artificial neural networks (ANN) is an expert system had been developed, which ANN was used widely with non-linear or long term data. The ANN modelling was used in several articles such as Behrang et al [2], had presented ANN for predicting daily global solar radiation (GSR) on a horizontal surface at Dezful city in Iran, based on meteorological variables, using different artificial neural network (ANN) techniques. The result shown that the best

* Corresponding author: S. Hongkong
E-mail address: hongkong_s@yahoo.com

Nomenclatures

ANN	artificial neural network
CIE	Commissioner Internationals de l'Eclairage
Eeg	solar global irradiance on horizontal surface ($W.m^{-2}$)
Eed	solar diffuse irradiance on horizontal surface ($W.m^{-2}$)
Eot	equation of time
Evg	solar global illuminance on horizontal surface (klux)
Evd	solar diffuse illuminance on horizontal surface (klux)
E_{mean}	average of data from measured ($W.m^{-2}$ or klux)
E_{meas}	measured data ($W.m^{-2}$ or klux)
E_{est}	estimated data ($W.m^{-2}$ or klux)
LT	local time (hr)
GSR	global solar radiation
GUI	graphic unit interface
L_{st}	standard Longitude
L_{lo}	longitude special local
MAE	mean absolute error (%)
MAPE	mean absolute percentage error (%)
MBD	mean bias deviation (%)
MLP	multilayer perceptron
AOS	adaptive observation system (%)
RMSE	root mean square error (%)
RMSD	root mean square deviation (%)
R^2	coefficients of determination
SR	sky ratio
ST	solar time (hr)
WT	watch time (hr)
y	output of function
w	weight in ANN model
x	input of function
b	bias value of ANN model
d	declination angle
h	hidden layer
i	unit of input layer
j	number of neuron in hidden layer
k	nodes of output layer
n	number day of the year
o	output data
t	target data

Greek Symbols

α	solar altitude angle (radians)
f	transfer function
ω	solar hour angle (radians)
δ	error term of ANN
η	rate of training ANN

the ANN model by use the day, mean air temperature of daily, sunshine hours, relative humidity and wind speed as inputs. The GSR of daily as output, the result of this model has MAPE about 5.21% .Voyant et al [3] used ANN for predicting daily solar radiation, by study the contribution of exogenous meteorological data to an optimized MLP in order to predict solar energy (multivariate forecasting).

In the Thailand, ANN modeling for estimating sky luminance has proposed by Janjai and Plaon [4]. The ANN model had trained with back propagation algorithm, based on 2-years data for predicting sky luminance of all sky conditions. The result shown that the ANN model can predict better than CIE models.

The ANN for estimation of solar radiation with different input parameters has presented by Koca et al [5]. 1-year data were used for training and 3-years were estimated. The number of input parameters was tested on solar radiation that was output layer and change input layer parameters from 2-6 parameters. The results shown that the number of input parameters was the most effective parameter on estimation of future data on solar radiation.

Hasni et al [6] proposed an estimating global solar radiation using artificial neural network and climate data. The LM algorithm with 3 neurons in the hidden layer of the network has produced the best results. The month, day, hour, temperature and relative humidity value were used to predict the global solar radiation. The results given the RMSE, MAE and R^2 for testing were 0.17, 2.99 and 0.99, respectively.

Notton et al [7] presented an ANN model for calculating global solar irradiation from global horizontal irradiation has only been a difficult task, especially when the time step is small and the data not averaged. The ANN is optimized and tested data of 5-year. The accuracy of the optimal configuration RMSE around 6% and RMSE around 3.5%, and found that this method can predict better than the empirical correlations available. In addition, ANN-based modelling and estimation of daily global solar radiation data proposed by Benghanem et al [8], air temperature and relative humidity had been used for estimating proposed by Shafiqur [9].

In addition, The ANN models were used for predicting solar radiation, such as the ANN was used for predicting solar potential assessment with various meteorological parameters [10]. ANN was used to combine with Fuzzy Logic in part of adjusting input variable for predicting ANN model [11]. ANN was used for predicting the horizontal global solar radiation with different combinations of meteorological parameters [12].

Aforementioned of the lecturer review, the different meteorological parameters have been used for estimating the global and diffuse solar irradiance, global and diffuse solar illuminance. However, the new input variables with adaptive observation for predicting not see in the review. The aim is of this study was the development of ANN modeling with input variables from detection of the sky condition consist of sky classification and solar altitude angle. The graphical user interface (GUI) had developed for using in control to monitor.

2. Concept of estimation

The concept for predicting of solar irradiance and illuminance on a horizontal surface in this study was used artificial neural network (ANN) with 2-input parameters and 4-output parameters. The prediction composed of three parts. First, synthetic of the ANN model by using data from standard instrument, 2- year for training and the trained ANN model was used MLP and Backpropagations with 10 neurons, one hidden layer. The transfer function of input layer use nonlinear function and output transfer function use linear function. The training function had based on the BFGS Quasi-Newton optimization. Second, calculate input variables from the adaptive observation system (AOS), which was system for detecting of all sky conditions to sky ratio, signal from electronic circuit with data acquisition to standard signal (0-1 Voltage). Finally, Predict and represent data on graphical user interfaces (GUI) in a format of numerical and graphical. The Fig.1 show diagram of this study.

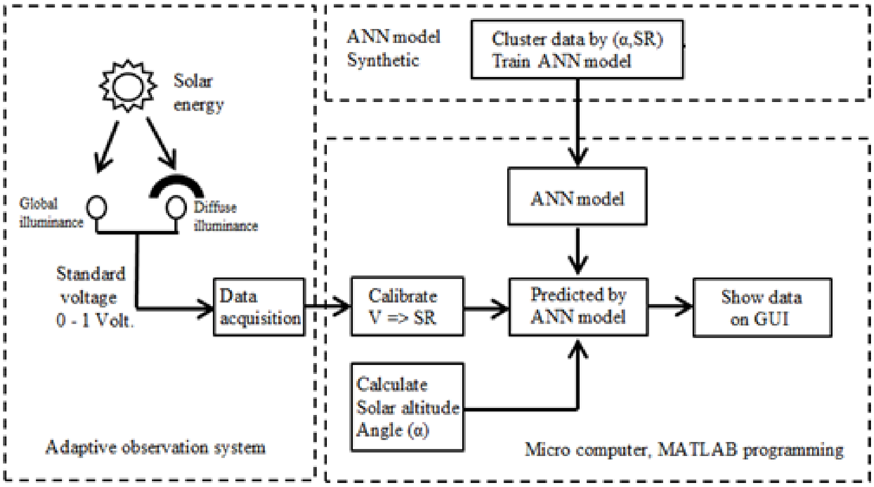


Fig. 1. Diagram for predicting solar irradiance and illuminance

3. DATA EXPERIMENTAL

The data of global, diffuse horizontal illuminance and irradiance had been recorded at Rajamangala University of Technology Isan, Sakonnakhon Campus, Thailand. Since 2015 - 2017 were recommended by CIE-standard [13]. The site is located at latitude 17.36 N and longitude 103.71 E. The solar irradiance and illuminance measuring equipment were supplied by Eko of Japan, instrument list was shown in Table 1.

Table 1: Specification of equipment.

Sky quantities	Detail		
	Sensitivity	**Accuracy**	**Measuring range**
Global illuminance	0.206 μV/ lux	2.1 %	0 - 150 klux
Diffuse illuminance	0.206 μV/ lux	2.1 %	0 - 150 klux
Global irradiance	7.03mV/ W. m^{-2}	2.3 %	0 - 1.5 kW. m^{-2}
Diffuse irradiance	7.03mV/ W. m^{-2}	2.3 %	0 - 1.5 kW. m^{-2}
Data logger	Standard data acquisition; Accuracy 0.5%		

4. ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) is computational models. The ANN consist of a large number of interconnected neurons. Each neuron is capable of performing only simple computation [11]. The ANN have been successfully used in solving complicated problems in different areas of application, including, image, control systems, classification, speech, and pattern recognition [6]. The ANN has a parallel-distributed structure and consists of a set of processing elements called neurons [7]. The ANN structure consists of:

- Input layer, which receives data.
- Output layer to send computed information.
- One or several hidden layers connect to input and output.

4.1 Multilayer perceptron (MLP)

The multilayer perceptron (MLP) were the most common format of feed-forward networks [14]. The Fig.2 show architecture of MLP with three layers has used in this research. The first is an input layer. The second is an output layer and finally is hidden a layer. The hidden layer will be consisting multilayer perceptron with 10 neurons. The neurons of input layer only act as buffers for distributing the input signals x_i to neurons in the hidden layer. Each neuron j (Fig. 3) of the hidden layer sums input signals x_i after weighting them with the strengths of the respective connections w_{ji} from the input layer and calculate output y_j as a transfer function.

$$y_j = f(\sum w_{ji} x_i - b_j) \tag{1}$$

f was transfer function such as radial basis function, hyperbolic tangent function or a sigmoidal function. The output data of neurons in the output layer are calculated similarly. The backpropagation algorithm, a gradient descent algorithm, is the most commonly adopted MLP training algorithm [15].

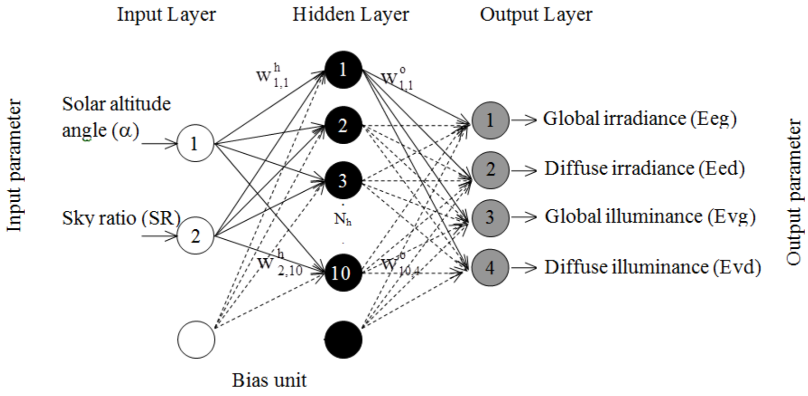


Fig. 2. The Architecture of multilayer perceptron with 10 neurons, one hidden layer has employed used in the research.

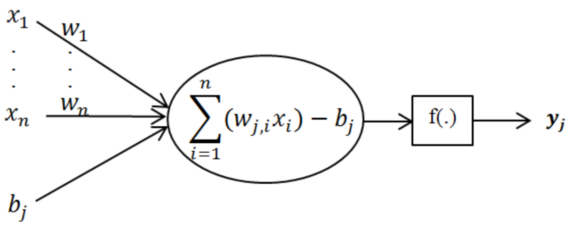


Fig. 3. Details of a neuron.

4.2 MLP training algorithm

The two years data for ANN training had defined input and output parameters. 2-input parameters were sky ratio and solar altitude angle) and 4-output parameters consists of global irradiance, diffuse irradiance, global illuminance, diffuse illuminance from 1/1/2015 to 31/12/2016.

The structural practice for the multilayer neural network by using back propagation algorithm, which activated the function of the input to the nonlinear function (select from: hyperbolic tangent sigmoid function; Tansig : y = 2 / (1 + e^{-2x}) - 1 or log-sigmoid function; Logsig : y = 1 / (1 + e^{-x}). The function of output layer using linear function (Purelin; y = x). The practical procedure of this neuron model used the following:

1. Randomly chosen weight.
2. Set up an example for the input layer, calculate the output of the perceptron in the hidden layer, and then output layer.

Calculate standard deviation to adjust the weight. For each network output unit k, calculate its error term δ_k :

$$\delta_k = o_k(1-o_k)(t_k-o_k) \tag{2}$$

For each hidden unit h, calculate its error term δ_h :

$$\delta_h = o_h(1-o_h)(\sum_{k\in output} w_{kh})\delta_k \tag{3}$$

3. Update each network weight: w_{ij}

$$w_{ji} = w_{ji} + \Delta w_{ji} \tag{4}$$

Where; $\Delta w_{ji} = \eta \delta_j x_{ji}$

4. Repeat step 2 until the total amount of the error is nearest to zero

When o_k is the output that was calculated at k level, t_k would be the real output for k level. δ_k is the error at k level, so δ_k is the error at 'h' level, η is the learning value x_{ji} is the vector of the input, and w_{ji} is the vector of weight. Vector of weight can be adjusted by using back propagation algorithm, which mostly affected in errors for practicing the structural model to $E(\overline{w})$, the least value of vector can be calculated as the equation below.

$$E(\overline{w}) = \frac{1}{2}\sum_{d\in D}\sum_{k\in outputs}(t_{kd} - o_{kd})^2 \tag{5}$$

The output is a function of output nodes, t_{kd} and o_{kd} represents the target output and output from the structure of output nodes at k of the sample d. Back propagation algorithm would search for the vector of weight, which gives the least error.

4.3 ANN model variation

An appropriate ANN modeling will be modifying the number of neurons in the hidden layer from 1-20 neurons. The same data of input (SR,α) had used for training and testing. The transfer function of the input layer to hidden layer used two functions were Tansig and Logsig functioning. The transfer function of hidden layer to output layer will use linear function. The testing for ANN modeling synthetic show in the Table 2. Whereof the number of neurons increase from 1 to 20 found that the value of MBD and RMSD for testing was close to zero and R^2 has close value of 1. The increase in the number of neurons up to 15 or 20 shows that the values of MBD and RMSD are very different from those of neurons, while R^2 is close to neurons of 10. Therefore, this research is to use the number of 10 neurons. The comparison between transfer function found that the Tansig function had better the Logsig function.

Table 2: ANN modelling synthetic of one hidden layer.

Number neuron	**Tansig : y = 2 / (1 + e^{-2x}) - 1**			**Logsig : y = 1 / (1 + e^{-x})**		
	MBD	**RMSD**	**R^2**	**MBD**	**RMSD**	**R^2**
1	-2.0693	21.657	0.86558	-0.77669	16.83	0.92376
2	-1.0467	7.0868	0.98668	-0.39277	6.1394	0.99061
3	-0.63022	4.6175	0.99434	-0.32835	5.6965	0.99122
4	-0.30663	2.4555	0.99841	-0.0416	2.8578	0.99801
5	-0.25445	2.5193	0.9983	-0.08078	2.1335	0.99886
10	**-0.01036**	**1.8551**	**0.99907**	**-0.04224**	**2.1547**	**0.99875**
15	-0.01728	1.149	0.99964	0.048901	1.2234	0.99960
20	-0.01785	0.9456	0.99976	0.037603	0.85874	0.99980

4.4 Testing

The new input parameters of sky ratio and solar altitude angle will be used for predicting, sky ratio had calculated from the AOS, the output voltage from electronic circuit system will be convert to sky ratio with calibrated. The solar altitude angle calculated from the sun position at latitude and longitude with solar time, which new data for testing model use data 1 year from 1/1/2017 to 31/12/2017.

5. Adaptive Observation System (AOS)

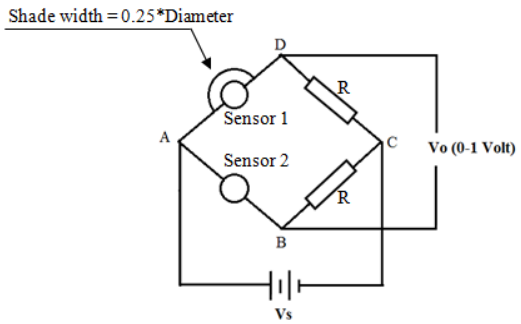
The sky ratio (SR) and solar altitude angle (α) were variables for predicting sky irradiance and illuminance. The adaptive observations system (AOS) is detection system of all sky condition changing by use electronic circuit convert to sky ratio. Which the solar altitude angle can calculate from time of the day at longitude and latitude. The new input variables will sand to testing ANN-model defined by:

5.1 Sky ratio

Normally, the sky brightness are categorized into three sky types: clear sky, partly cloudy sky and overcast sky [16]. The indices which are used for classifying the sky types, the relationship of these indices may calculate from equations 6. The sky ratio has originally been defined as the proportion of the diffuse radiation (Eed) to the global radiation (Eeg) and used in the estimation of solar radiation. Another way be calculated sky ratio from the diffuse illuminance (Evd) to the global illuminance (Evg). Theoretically, when the sky is completely overcast the values of sky ratio should be 1.0 [17]

$$\text{Sky Ratio (SR)} = \frac{\text{Evd}}{\text{Evg}}; \quad \text{or} \quad \text{SR} = \frac{\text{Eed}}{\text{Eeg}} \tag{6}$$

The detection of sky ratio value in this article, will use the circuit in Fig. 4(a) by setup at sun tacker as show in Fig. 4(b) below.



(a) Bride balance circuit

(b) Prediction

Fig. 4. Bride balance circuit for detecting ratio of Diffuse/Global illuminance

The sensor for detect of solar illuminance use lighting dependent resistant, by connecting follow as : the sensor 1 have a shade with width equal 0.25*D (D is diameter) for receiving the solar diffuse illuminance and one no shade for receiving the solar global illuminance. When the sky condition is clear sky, voltage output should nearly 1 Volt. While the sky condition is overcast sky, voltage output should 0 Volt.

5.2 Solar altitude angle

The second observation value is a solar altitude angle, which the sun's position in the sky at one point on the earth at a particular time of the day (Fig. 5). The calculation of solar altitude angle can fine below [18].

$$\text{Local time (LT)} = \text{Watch time (WT)} \pm \Delta \tag{7}$$

$$\Delta = 4(L_{st} - L_{lo}) \tag{8}$$

Where; LT is the Local time, WT is the Watch time, L_{st} is the Standard Longitude and L_{lo} is the Longitude from special local. Equation of time follows from equation (9)

$$EoT = 9.87\sin(2B) - 7.53\cos(B) - 1.5\sin(B) \quad (9)$$

Where; $B = (360/364)\times(n-81)$ and n is the number day of the year. So that solar time can find below.

$$\text{Solar time (ST)} = \text{Watch time (WT)} \pm \Delta + Eot \quad (10)$$

The declination angle, d may defined as the angle between the line joining the centers of the sun.

$$d = 23.45\sin\left(\frac{360(284+n)}{365}\right) \quad (11)$$

Solar hour angle, ω it is the angle through which the earth must be rotated to bring the meridian of the plane directly under the sun. It can find from the equation (12)

$$\omega = 15(t-12) \quad (12)$$

Where; *t* is the solar time. Solar altitude angle, α can find.

$$\sin\alpha = \cos\ell\cdot\cos\omega\cdot\cos d + \sin\ell\cdot\sin d \quad (13)$$

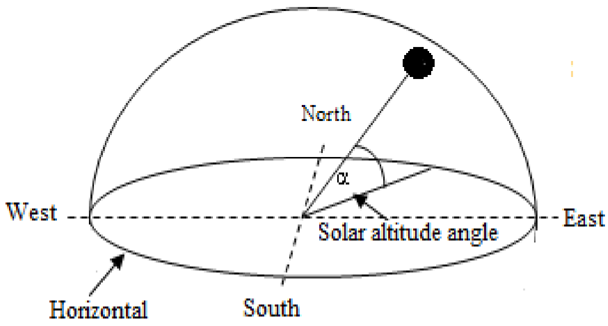


Fig. 5. Solar altitude angle

6. RESULTS AND DISCUSSION

The result of prediction global, diffuse solar irradiance and illuminance on a horizontal surface by using an ANN model with adaptive observation system found that the sky condition is overcast sky, the sky ratio is gets close 1. The sky condition is clear sky, sky ratio gets close 0. The sky ratio is the input variable.

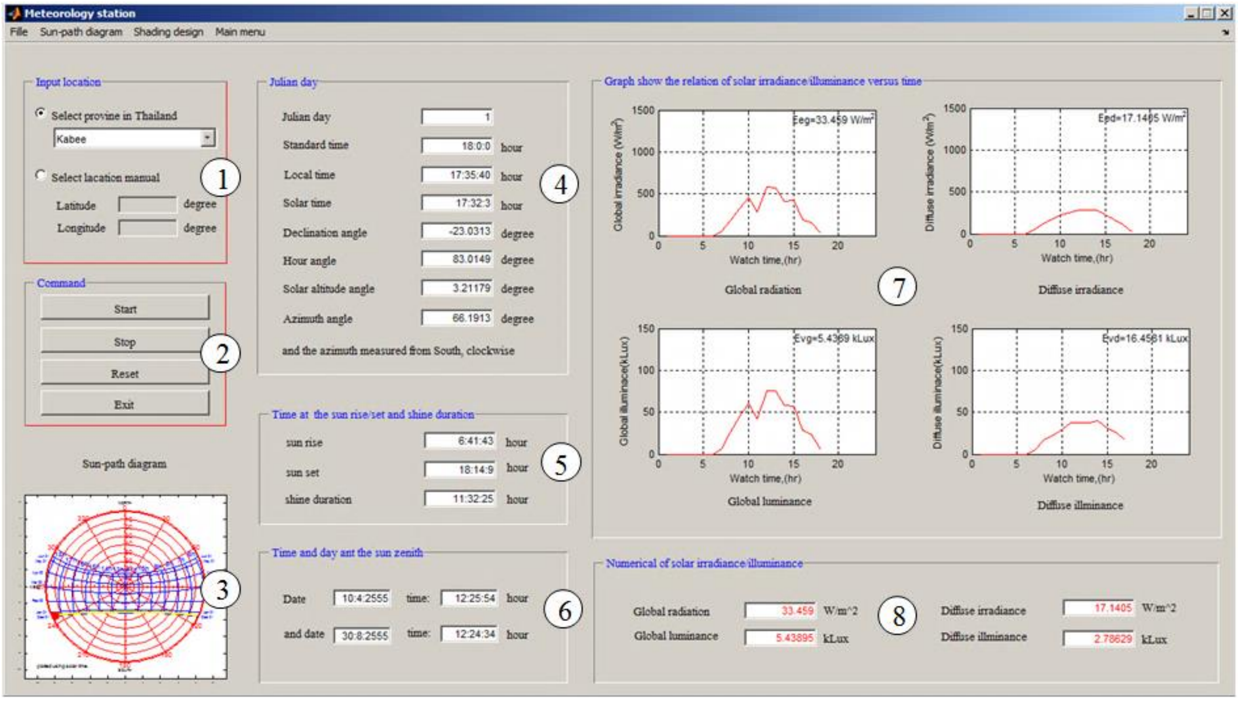


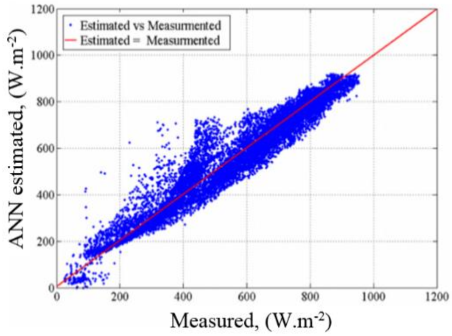
Fig. 6. Graphical Unit Interfaces for represents the result of prediction.

The Fig.6 show the graphical unit interface (GUI) for estimation solar energy, which consist of: Number (1) is select location in province of Thailand or defines the latitude and altitude. Number (2) is a command button for user. Number (3) is Sun-path diagram show sun position bots the year and sun position at the moment time. Number (4) is result of estimation such as: Julian day, Standard time, Local time and etc., Number (5) is show time when sunrise and sunset. Number (6) is the date and time at the position when sun zenith. Number (7) shows data from estimation in graphical, and Number (8) is the result of estimating the numerical format. The result of testing of the model takes in 2017, the new input from an adaptive observation system has sent to ANN model. The result from prediction has recorded on computer and save file follow as: (date: mount: year) on text file format. Table 3 shown data evaluated about model, found that the data from prediction by using an adaptive observation system with ANN-based model compares with data measured by standardize measurements were represent by tree statistical MBD, RMSD and R^2. The Fig.7 shown plotting of measured versus estimated data, which ANN model by using input with adaptive observation system can estimated data of solar global, diffuse irradiance and solar global, diffuse illuminance for all sky condition.

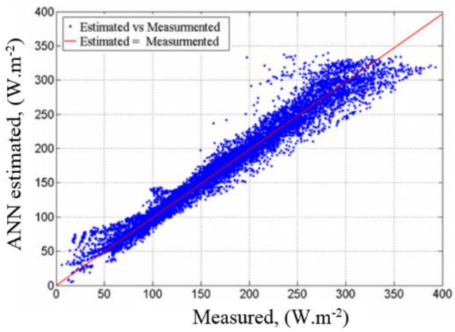
Table 3: Summary statistical parameters for MBD, RMSD and R^2

Statistical analysis	Global irradiance, (W.m^{-2})	Diffuse irradiance, (W.m^{-2})	Global Illuminance (klux)	Diffuse Illuminance (klux)
MBD (%)	0.1188	0.3477	0.0102	0.1335
RMSD (%)	8.8131	10.8020	6.0700	11.6410
R^2	0.9791	0.9647	0.9865	0.9497

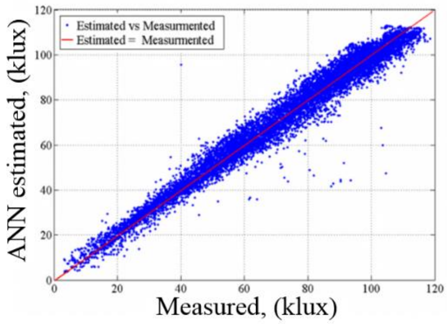
The Fig.8 shown contour plot of solar global and diffuse irradiance, solar global and diffuse illuminance were predicted from ANN modelling with adaptive observation system. The result shown that level of global irradiance and illuminance were high during from April - May. The diffuse of irradiance and illuminance were high in June - September, this is due to the rainy season send to diffuse irradiance and luminance is very high. The most of sky condition were overcast skies send to the sunrays were collide with the cloud and reflect so much.



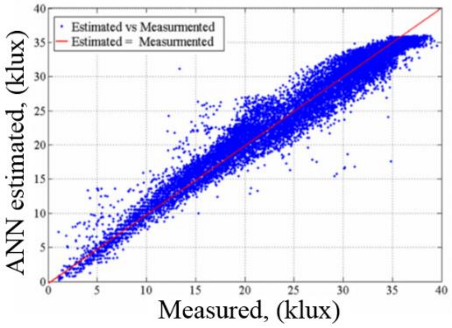
(a). Global irradiance



(b). Diffuse irradiance

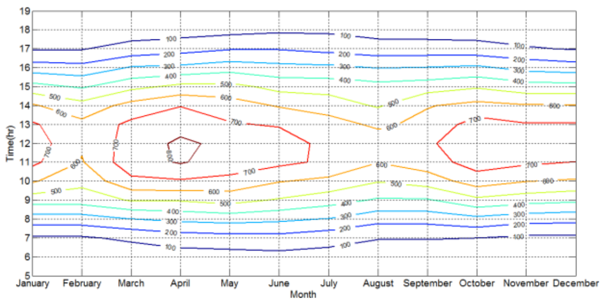


(c). Global illuminance

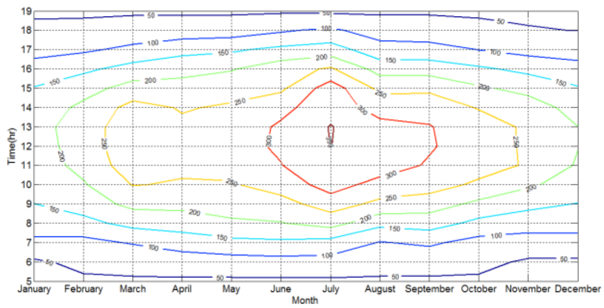


(d). Diffuse illuminance

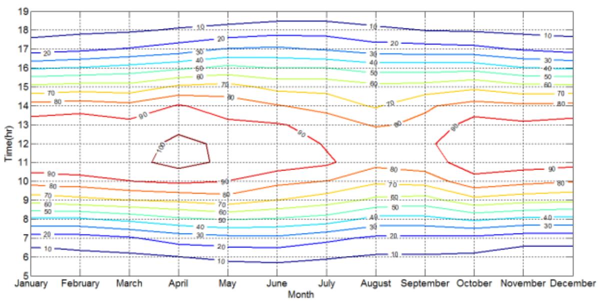
Fig. 7. Measured versus estimated



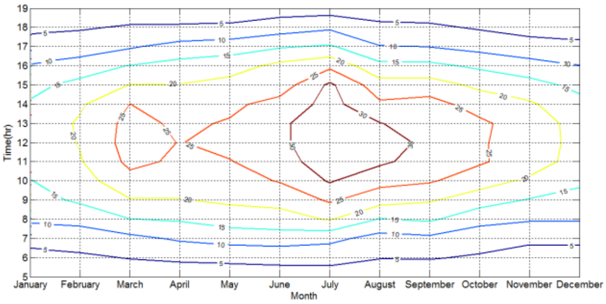
(a) Global irradiance (W/m^2)



(b) Diffuse irradiance (W/m^2)



(c) Global illuminance (klux)



(d) Diffuse illuminance (klux)

Fig. 8. Contour plot of data from ANN-based on adaptive observation system

7. Conclusion

The artificial neural network (ANN) has developed for predicting solar energy. This article presented a novel technique for predicting by use adaptive observation system (AOS). The AOS was system for detection input parameters as real time. Input parameters of ANN model were consist of sky ratio (SR) and solar altitude angle (α), output parameters were consist of global, diffuse solar irradiance and illuminance. The trained ANN model was used MLP and Backpropagations with 10 neurons, one hidden layer. The transfer function of input layer use hyperbolic tangent sigmoid function and output transfer function use linear function. The training function had based on the BFGS Quasi-Newton optimization. Data recorded from 2015 to 2016 for training ANN modelling, 1-year new data in the 2017 for predicting of solar irradiance and illuminance with adaptive observation system. The comparisons between the predicted and measured data shown relative of statistical with MBD, RMSD and R^2. The graphical user interfaces (GUIs) has developed for using, which will show data in numerical and graphical on GUIs. The advantage can be use this technique for predicting about data weathers and this method can decrease problem of an instrument was expensive.

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Appendix

Appendix A: Statistical analysis

We determine the accuracy of model validation by using three statistical indexes: Mean Bias Deviation (MBD), Root Mean Square Deviation (RMSD) and Coefficients of Determination (R^2). The relationship of those equations are expressed as equation (14) to equation (16)

$$\mathrm{MBD} = \frac{\sum_{i=1}^{n}(E_{est,i} - E_{meas,i})}{n \cdot E_{mean,meas}} \tag{14}$$

$$\mathrm{RMSD} = \left(\frac{1}{E_{mean,meas}}\right) \cdot \sqrt{\frac{\sum_{i=1}^{n}(E_{est,i} - E_{meas,i})^2}{n}} \tag{15}$$

$$R^2 = \frac{\sum (E_{est} - E_{meas})^2}{\sum (E_{meas} - E_{mean})^2} \tag{16}$$

Where; E_{mean} is average of data from measured, E_{meas} is measured data, E_{est} is estimated data, n is number of records of data for testing, MBD shows the model inclination, RMSD explain short-term of error and R^2 show the relation between estimated and measured.

Appendix B : Artificial Neural Network model

Input weight [10×2]

-6.9849	-7.3562
22.7173	5.0383
-12.3484	-7.0641
0.8399	-10.0821
12.1355	10.7222
-23.9573	10.3284
-0.0295	16.8937
-23.0545	-16.9704
-3.2691	11.9218
-6.4983	19.1530

Input bias [10×1]

-31.3992
30.5935
-23.5329
-24.2303
-29.9492
-26.3335
-9.9481
16.4306
-13.6651
-5.0653

Hidden Layer weight [4×10]

-40.7448	38.1680	-40.5579	45.9707	42.3464	-40.0005	-37.6742	-39.9825	-41.1809	-41.6095
-11.7679	10.8138	-13.9069	11.3020	14.6990	-11.5137	-14.8549	-13.4821	-18.2220	-14.6151
-3.8217	7.7802	-4.4089	6.0273	2.4501	-8.3154	-7.1719	-3.6733	-5.4416	-4.0597
-1.1178	0.4622	-6.3311	0.9489	1.1607	0.2798	-3.9455	-6.6704	-1.5477	0.6403

Output bias [4×1]

43.6332
17.6161
5.2230
1.9112

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