Prediction Photovoltaic Rooftop Energy Based on Artificial Neural Network Related with a Solar Site Survey

K. Khongseeprai[1], B. Wangngon[1], and S. Ruangsinchaiwanich[1,*]

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ABSTRACT.

The growth of photovoltaics (PV) is significant. Because both PV technology has been improving continuously and PV cost has been falling potentially. In Thailand, PV rooftop has been encouraged to employ to buildings particular city center, since it requires no additional land use. However, there are many factors that affecting the operation and efficiency of the PV based electricity generation systems, the forecasting methods of the solar power generation have been deliberated by many solutions. Recently numerous methods have been proposed in order to forecast the solar radiation forward to predict power generation. In this paper, an artificial neural network (ANN) is proposed for predicting PV rooftop power. Also main input variables are considered as high relation of solar radiation, for example, altitude angle, azimuth angle, humidity, temperature, and day time. Additionally, the proposed method is adopted using artificial neural network with multilayer feed forward method for estimating electric power generation of photovoltaic solar rooftop according to the dataset of the PV plant at Phitsanulok, Thailand. Consequently, the electrical power output of PV rooftop can be estimated as following the proposed model. Therefore, the resultant comparison is presented which exhibited a decent evident that a solar site survey can be effect the error of the estimation either incorrect position or shading condition

1. INTRODUCTION

Significantly the solar energy is recognized as one of renewable energy sources, since the solar manufacturing and installation process have been becoming highly professional that their competitions are tremendously, therefore the solar energy becomes the cheaper source of electricity comparing with other energy sources. Also precise comprehension of the solar radiation data is discussed as the first step in solar energy availability assessment. It has been employed as the input for many solar energy applications, however its convolution is reviewed on a regular basis due to the high cost of measuring equipment and their maintenance. Generally, the electric energy yield of photovoltaic (PV) system is related positively to several weather conditions for example solar irradiance, temperature and dust. Furthermore, the altitude and azimuth angle of PV installations play a major role in increasing the annual energy yield production. In 2018, an analysis of the optimum tilt angle PV panels is suggested that between 25.89º to 26.06º are the optimum tilt angle for PV modules in dusty weather conditions in twenty-six locations within the county of Yorkshire, UK. [1]. Also many methods have been deliberated to improve forecasting PV models, for example output errors of hybrid photovoltaic power forecasting models such as the least square support vector machines, artificial neural network (ANN), and hybrid statistical model, were studied that can also evaluate the performance of PV output [2]. Definitely sunshine time duration is main one of input parameter for predicting PV output, the performance of simulation can be reached to more than 5.5% of error and the spectral influence on photovoltaic based instrument can be neglected to some extent [3]. Evidently the data of solar irradiance with standard instrument collection is significant for assisting to illustrate a PV installation with decent local positioning [4]-[8]. For example, sunshine duration, humidity, precipitation and temperature can be applied to input to ANN model for estimating PV output of electrical power per month that the mean average percentage error was lower than six percent in order to using local conditions [10]. Moreover, some researcher suggests the detail error of PV power forecasting models, which is certainly ANN model, can be reduced by using hybrid consideration [11].

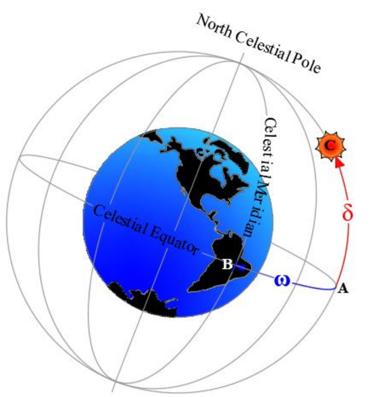
In this paper, the artificial neural network is approached for estimating solar power output of PV rooftop systems in the area of Phitsanulok, Thailand, since it is a knowledgeable system and is used to solve complex

[1] *Department of Electrical and Computer Engineering, Faculty of Engineering, Naresuan University, Phitsanulok, 65000, Thailand.*
**Corresponding author:* S. Ruangsinchaiwanich; Phone: +66-869-255-005; Email: sompornr@nu.ac.th.

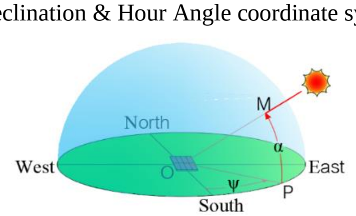
problems in many applications for example optimization, prediction, simulation, pattern recognitions, investigation, and others [1-2], [9]-[15]. This proposed artificial neural network model is designed for using relation between for example solar radiation value, relative solar altitude angles of solar radiation, local weather condition, and its corresponding electrical power with the discussed literatures.

2. SOLAR ORIENTATION

Generally, the electricity output value for a PV panel can be estimated by several parameters for example solar radiation, and atmospheric conditions. For solar radiation, there are two main factors for example the direction, and the tilt angle that are independent. Apparently, the relative solar altitude angles of solar radiation at a certain point is the significant indicator to approximate the electrical energy generation from a PV panel [1][9]. Moreover, atmospheric conditions of the local location which is Phitsanulok Province, Thailand, are average temperature, relative humidity, wind speed and mass air [10-11].



(a) Declination & Hour Angle coordinate system.



(b) Altitude & Azimuth coordinate system.

Fig. 1. Position of the sun relative to the surface of the earth.

For figure 1, solar altitude angle (α) is the angle between the horizontal and the line to the Sun (OM) that can be defined ($0° \leq \alpha \leq 90°$). Also solar azimuth angle (ψ) is angular displacement from south of the projection of beam radiation on the horizontal plane. Normally, $\psi = 0$ equals south, $\psi < 0$ is east, and $\psi > 0$ is west. Nevertheless, different references could be found. There are arranged as:

$$\alpha = \sin^{-1}(\sin\phi\sin\delta + \cos\phi\cos\delta\cos\omega) \tag{1}$$

$$\psi = \sin^{-1}\left(\frac{\sin\omega\cos\delta}{\cos\alpha}\right) \tag{2}$$

Since these two angles have been recognized [4], it assistances to describe the solar radiation accessing every location on Earth. There exist two main ways to determine the Sun position on the sky through the solar altitude angle and the solar azimuth angle through the equation 1 and 2 that both options may be involved geographically with information on latitude (ϕ), declination (δ) and hourly angle (ω). There are geographically angles, consequently for local PV station that consider for forecasting PV power estimation, the precise angles are required according to lead to more faithful results.

Table 1. Installation of solar roof at each building

Building	Number of PV (Panel)	PV Direction	PV Tilt
A	120	South	9.9°
B	114	South	16.9°
C_1	39	East	30°
C_2	40	South	13°
C_3	39	South	30°

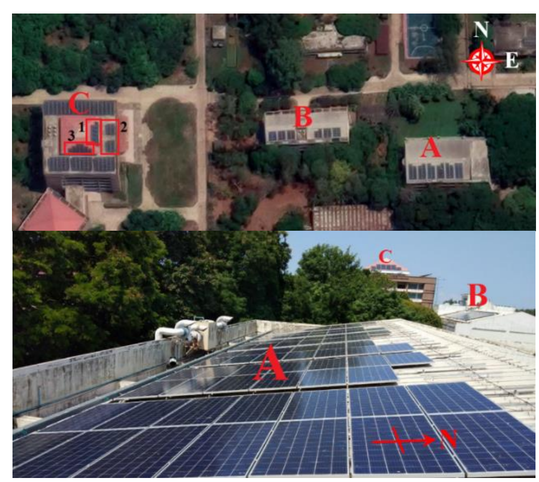


Fig. 2. Topview of solar rooftop on buildings at this study case at Phitsanulok Province, Thailand.

For this study, a PV rooftop prototype of solar power plant is off grid connection with PV type of crystalline solar cells. And the location of solar rooftop plant is at Phitsanulok, Thailand that with 16.861°N Latitude and 100.183°E Longitude. Also a fixed PV rooftop, area receiving solar radiation. The data of solar roof panel each building is shown in table 1. Furthermore, figure 2 shows either top view photo or actual PV rooftop of the experimental setup for geographical consideration for setting input parameters to this a proposed artificial neural network. Also figure 3 is displayed as a single line diagram of PV rooftop on grid for this study.

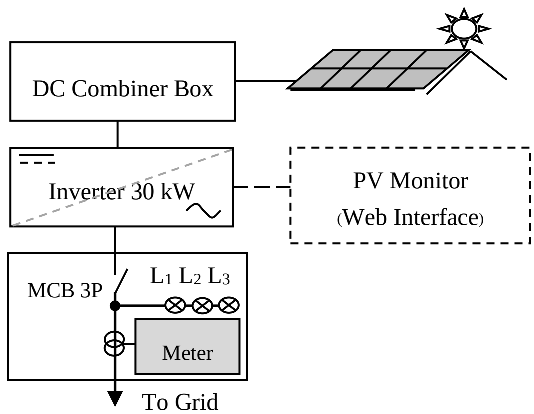


Fig. 3. Electrical system of single line diagram.

3. ARTIFICIAL NEURAL NETWORK

In this paper, an artificial neural network (ANN) is proposed to apply to estimate output of PV electrical power. It is one of artificial intelligence where it attempts to simulate the network of neurons as making up a human brain. Therefore, it is recommended for applying to several research fields [1-2], [9-10]. Also computers will have an option to understand things and make judgements in a human-like manner. Essentially, several parameters related with the electricity output value for a PV panel are considered for example solar radiation, and atmospheric conditions [14]. In this paper, the length of day time, the local average temperature, relative humidity, wind speed and mass air, declination, hour angle, the distance between the Earth and the Sun, solar altitude angle, and solar azimuth angle are firstly studied. In this step, correlation coefficient is considered for filtering inefficient input parameters to avoid surplus time calculation. Also, $\mathbf{R_{mean}}$ of input parameters, which are averaged with10 times of testing, are shown in table 1 that R>0.7 are preferred.

In this paper, an artificial neural network (ANN) is proposed to apply to estimate output of PV electrical power. Also the figure 4 illustrates procedure of the proposed neural network with the feed forward technique. Theoretically, the feed forward technique executes data in one direction subsequently there is no either cycles or returning loops in this technique that has advantage of speedy calculation. Fundamentally it consists observantly with an input layer and an output layer. Basically a first layer can be named as input layer that user can set input parameters for processing to start to estimate solar radiation. Significantly there are geographical this input parameters, for example solar altitude angle (α), solar azimuth angle (ψ), hour angle (ω), the local average temperature (T), the length of day time (DT), declination (δ), and the distance between the Earth and the Sun (E_0). However, there is significantly a hidden layer and suitable to connect the input and output layer. Moreover, the log-sigmoid transfer function is applied with 10 neurons. The last layer can be called as output layer that transfer function is the linear function that the solar radiation estimation (G_E) is targeted confidently for the local precise condition. Therefore, in order to roughly estimate the electrical solar energy output from PV rooftop system can be designed as shown in figure 5.

Table 1. Correlation coefficient (R) between parameters and solar radiation

Variables	R_{mean}	S.D.	Meaning
Day time (DT)	0.774	0.046	High
Average temperature (T)	0.887	0.006	High
Relative humidity (H_R)	0.544	0.046	Medium
Wind speed (W_S)	0.552	0.072	Medium
Mass air (m_a)	0.633	0.019	Medium
Declination (δ)	0.746	0.057	High
Hour angle (ω)	0.795	0.050	High
The distance between Earth and Sun (E_0)	0.759	0.015	High
Altitude angle (α)	0.763	0.040	High
Azimuth angle (ψ)	0.787	0.021	High

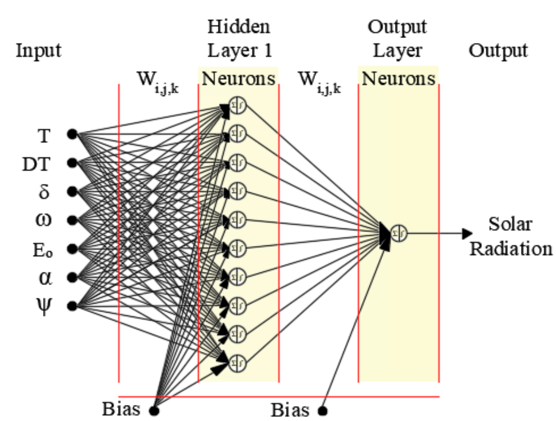


Fig. 4. This proposed artificial neural network diagram.

Figure 5 shows the study process starting from the study of input parameters related to solar radiation and using these ones with a statistical correlation coefficient (R) greater than 0.7, then all input parameters were estimated hourly solar radiation by ANN method using data during 8:00 a.m. 4:00 p.m. Once the estimated solar radiation value has been obtained, it will be used to calculate the power generation capacity. Therefore, for duration and amount of data used in various steps are shown in Table 2.

Section learning of ANN is divided into 3 parts: Training, Validation, and testing, divided into percentages of 70%, 15%, and 15%, respectively.

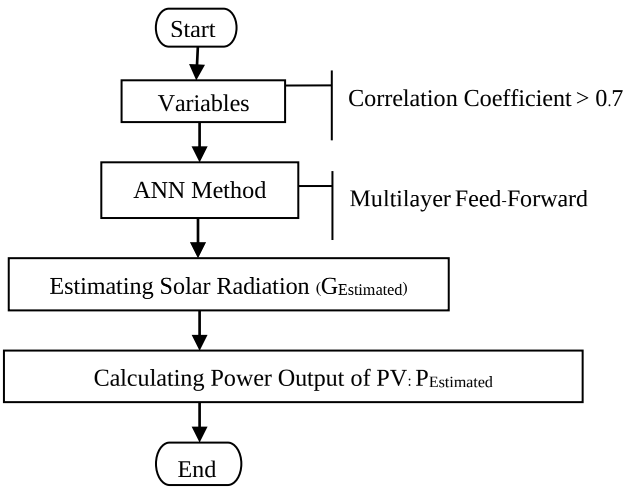


Fig. 5. Flowchart of this PV estimation.

Table 2. Data for Estimated $G_{Estimated}$ and $P_{Estimated}$

Algorithm	Period	Data
Learning of ANN	Dec. 1-31, 2018	198
$G_{Estimated}$	Dec. 1-31, 2019	207
$P_{Estimated}$	Dec. 1-31, 2019	207

For the input parameters can plot a scatter diagram by the ANN method for studying the correlation coefficient (R) is shown in Figure 6. It can see that the correlation coefficient is more than 0.9, meaning that the seven input parameters and solar radiation have a high correlation. And when considering the error histogram in Figure 7. Further, it can be seen that it can be seen that most of the learning data has near zero error value.

There are several standard metrics used in model evaluation. For analyzing the accuracy of estimates were used statistical values mean absolute error (MAE), and mean absolute percentage error (MAPE) as shown in the following equation. Actually the MAE is one of useful measure which is broadly applied in model evaluation on particular climate research studies. While it has been applied to assess model performance for many years. Also MAPE is a metric that defines the accuracy of a predicting method. It characterizes the average of the absolute percentage errors of each entry in statistic to estimate how accurate the forecasted quantities were in comparison with the actual quantities [14].

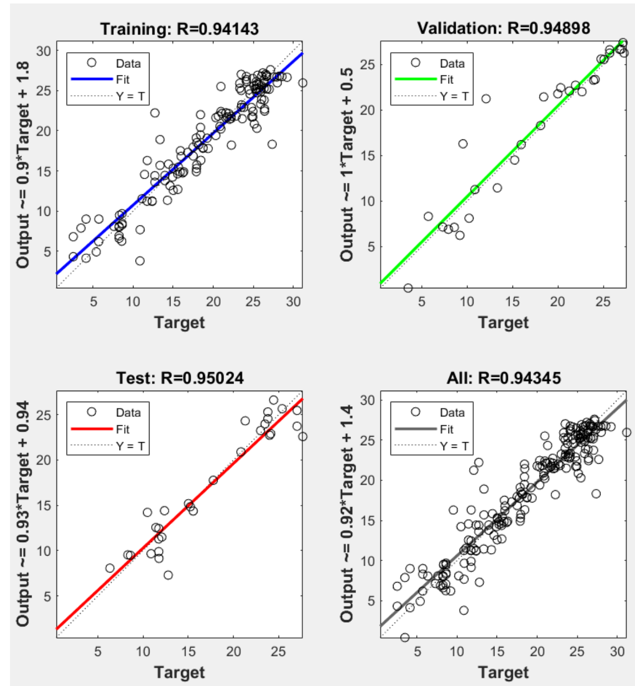


Fig. 6. The scatter diagram shows the relationship between the seven input parameters and solar radiation.

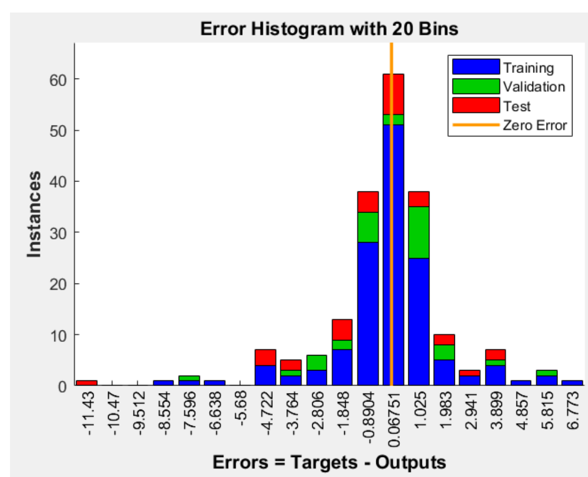


Fig. 7. Error histogram from learning of ANN.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - y_i'\right| \quad (3)$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - y_i'}{y_i}\right| \times 100\% \quad (4)$$

When y_i is measured values, y'_i is estimated values, and N is the number of target data.

4. RESULTS AND DISCUSSION

Since this proposed artificial neural network model is inserted with the proposed input data. For this step, the result of solar radiation was estimated (red line) compared to the measured value (black line), as shown in Figure 8, which is the solar radiation test at the B building which is no shading condition. It can consider that on the first day and the second day, which are the clear sky. The estimated solar radiation value was close to the actual measurement value. But on the third day, which is partly cloudy. Furthermore, the estimated solar radiation value has of error compared to the measurement value during the time when the cloud shadow is obscured.

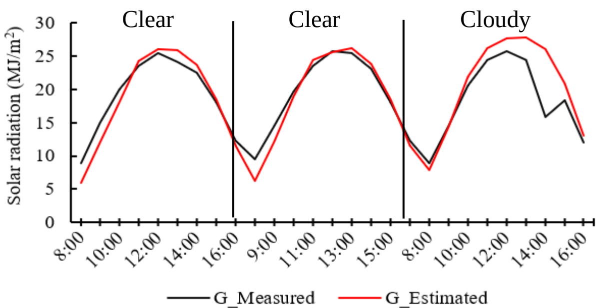
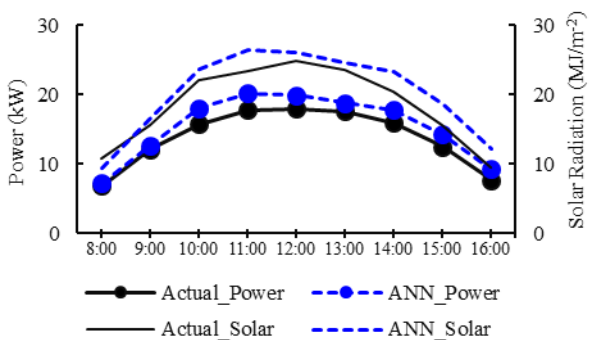
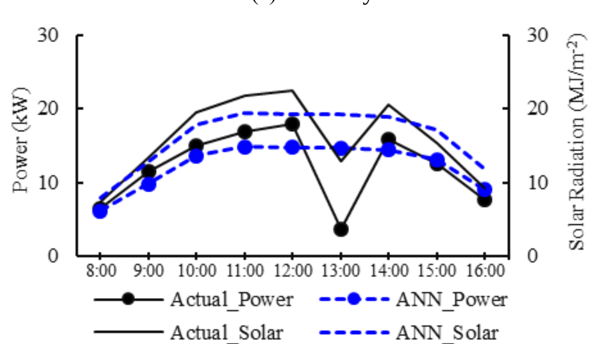


Fig. 8. Comparison of solar radiation between the measured value and the estimated value.



(a) Clear sky



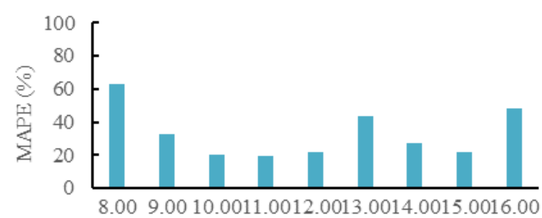
(b) Partly cloudy

Fig. 9. Comparison between measurement and estimation of the PV rooftop under the different weather at B building.

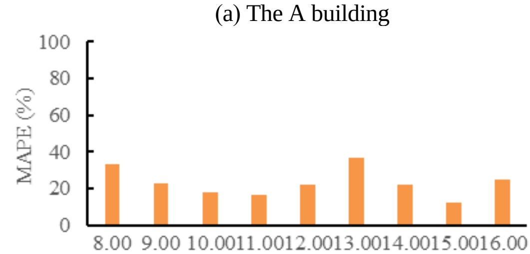
Table 3 shows the accuracy comparison of solar radiation estimate models under different weather in December 2020, between 18 days of clear weather and 5 days of partly cloudy. It can be seen that when considering the statistical values includes MAE, and MAPE. Firstly, the local solar radiation estimation of this ANN method on a clear day (12.211 % of the MAPE) is more accurate than solar radiation estimation of this ANN method on a partly cloudy day (24.134 % of the MAPE).

Table 3. Accuracy comparison of solar radiation estimate models under the different weather

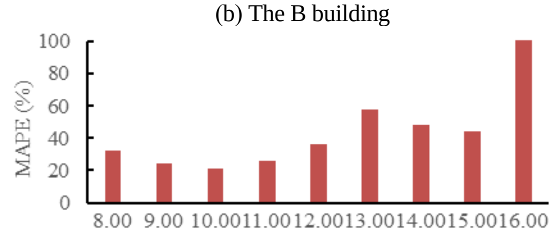
Weather Condition	MAE (MJ/m^2)	MAPE (%)
Clear sky	1.887	12.211
Partly cloudy	3.196	24.134



(a) The A building



(b) The B building



(c) The C building

Fig. 10. Comparison the MAPE of the power estimation of PV rooftop each building.

The power estimation of PV rooftop at the B building is continued to estimate the power with the proposed model. Also figure 9 (a) is shown the power estimation of PV rooftop at the B building, that the ANN estimation (the blue line) are compared with the actual power (the black line) with clear weather condition. It can be seen that results are good agreement from 8.00 to 16.00 as typical scheduling of the solar radiation in Thailand. Correspondingly figure 9 (b) is indicated the comparable results with partly cloudy condition. However, the solar radiation estimation results are slightly imprecise comparing with the solar radiation values obtained from the measurements. As a result, the estimated power generation has additionally a little error from the actual measured value. Further, it can be suggested that the occurrence of partial cloud shadows toward PV can result the error of solar radiation estimates.

Since MAPE can describe the accuracy of a predicting method [14], thus it is employed for describing this proposed for forecasting power estimation from the A building, the B building, and the C building that calculate the MAPE each hour as shown in Figure 10. Furthermore, table 4 is shown the total MAPE comparison of estimated power generation in December 2020. It can be confirmed that the MAPE of estimated power generation from the PV of the B building has the least discrepancy (19.001%). Because there is no problem of shading or facing the solar panel in a direction. However, the PV rooftop of the C building is installed as having difficulty, because of available rooftop area as shown in figure 11, which has panels and some solar panels facing shading condition. Therefore, the MAPE of the power estimation result at the C building are the most discrepancy (31.301%) that comparing to other building results.

Table 4. Accuracy of estimated power Generation for the PV rooftop of each building

Building	MAPE (%)
A	21.588
B	19.001
C	31.301

Fig. 11. Shading effect of building at the C Building.

5. CONCLUSION

For this paper, the proposed artificial neural network modelling was proposed to simulate the estimation of solar radiation with a site survey Phitsanulok, Thailand. For solar radiation, there are two main factors for example the direction, and the tilt angle that are independent. Actually, many parameters related with the electricity output value for a PV panel. However disorganized input parameters can devastate time calculation, therefore, correlation coefficient can be considered for filtering inefficient input parameters. In this paper, the length of day time, the local average temperature, relative humidity, wind speed and mass air, declination, hour angle, the distance between the Earth and the Sun, solar altitude angle, and solar azimuth angle are selected to be the input. Thus the electrical power output of PV rooftop can be estimated as following the proposed model. The resultant comparison is presented which exhibited a good evident performance. Again the artificial neural network is versatile for either simulating or estimating results that are different types of input data as they have capability to overcome certain uncertainties.

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