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# Estimating hourly global solar irradiance using artificial neural networks – A case study of Hong Kong

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**Abstract.** Solar energy is the most popular resource for power generation among the various available renewable energy alternatives. Solar radiation data are important for solar photovoltaic (PV) systems and passive energy-efficient building designs. Due to the unavailability of measurement in rural locations, solar radiation prediction models are required. In recent years, the Artificial Neural Networks (ANN) were successfully used for predicting solar radiation. However, previous works indicated that the ANN techniques were mainly focusing on prediction of monthly average or daily solar radiation, a few of them were modelled for predicting solar irradiance in hourly basis. In this study, prediction models of global solar irradiance on a horizontal surface will be developed based on neural-network techniques. Hourly meteorological variables between 2012 and 2015 acquired from the measurements made by local meteorological station were used for the study. To consider the effectiveness of individual predictors, different combinations of input variables were analysed using the Levenberg-Marquardt (LM) algorithm. Finally, equations were modelled by regression based on the important predictors. The developed models were used to estimate the global irradiance and assessed against measurement results.

**Keywords:** Global horizontal irradiance, ANN, Sensitivity analysis, Hong Kong

## 1. Introduction

Solar radiation data are important to active solar energy systems [1] and passive energy-efficient building designs [2]. It is a widespread concern to estimate the amount of such data at the specific location. Long-term ground measurement is the most effective and accurate way of setting up the databases of the required climatic parameters. However, many places do not offer measured solar radiation data [3]. Without direct measurement, the data can be predicted from empirical models based on geographical parameters and meteorological variables. Empirical prediction models tend to involve regression techniques, the principal merit of which is the simple format of mathematical expression [4]. The issue is that these simple models underperform if the systems being modelled are nonlinear. Recently, various Machine Learning (ML) algorithms, including Artificial Neural Network (ANN) and Support Vector Regression (SVR), have been used for estimating solar radiation [5, 6]. Models developed using these techniques tended to be more complex, less interpretable [7], and yet more accurate than regression equations [8]. More importantly, ML algorithm can be adopted to identify the contribution of individual input variables in the estimation of output in terms of mean-bias-error (MBE), root-mean-square-error (RMSE) and coefficient of determination ( $R^2$ ) [9]. Such approaches have been used of many problems with large datasets, large quantities of relevant variables and complex interrelationships between input and output variables [10]. This paper proposes an approach for calculating the horizontal global solar radiation. Sensitivity analysis of individual meteorological parameters in determining the global solar radiation was analyzed using ML techniques and regression equations were modelled based on the important parameters. The findings and building design



implications are discussed.

## 2. Solar irradiance and meteorological data

The horizontal global solar irradiance (GHI) levels and fluctuations are influenced considerably by the meteorological data. Available climatic parameters could be used as predictors to estimate hourly global solar irradiance. Different combinations of climatic parameters and geographical parameters were used in previous empirical models. The choice depends on the availability, accuracy and suitability of these climatic data.

Solar irradiance and meteorological data acquired from the measurements made by the Hong Kong Observatory (HKO) was used for the study. The three years hourly data from 2012 to 2014 were analyzed for the ANN models and regression models. It is inevitable that there are some short periods of missing data or some inaccurate data for various reasons. To eliminate spurious data and inaccurate measurements, quality-control tests based on the CIE guidance [11] were adopted. Table 1 summarizes the tests and results. Under Level 0 test, 1390 hourly irradiance data with a solar altitude of less than  $4^\circ$  or the GHI less than  $20 \text{ W/m}^2$  were rejected. Then, 4 and 1224 hourly data were excluded under Level 1 and Level 2 tests respectively based on the conversion relationship between the three aspects of irradiance. After all the tests, 10475 hourly solar irradiance and meteorological datasets were retained for the analysis. Table 1 summarizes the number of accepted and rejected data for each process.

**Table 1.** Data quantity control process

CIE test level	Criterion	Number of data record (Hour)	
		Rejected	Accepted
Total	Solar altitude $\alpha > 0$		13226
Level 0	Solar altitude $\alpha > 4$ ; GHI $> 20 \text{ W/m}^2$	1390	11836
Level 1	$0 < \text{GHI} < 1.2 * \text{GHE}$ ; $0 < \text{DHI} < 0.8 * \text{GHE}$ ; $0 \leq \text{DNI} < \text{GHE}$	4	11832
Level 2	$0.9 * (\text{GHI} - \text{DNI} * \sin \alpha) < \text{GHI} < 1.1$ $* (\text{GHI} - \text{DNI} * \sin \alpha)$ ; $\text{DHI} \leq \text{GHI}$	1224	10608
Level 3	Effective record of meteorological parameters	133	10475

GHI: global horizontal irradiance; GHE: extraterrestrial solar irradiance; DNI: direct normal irradiance; DHI: diffuse horizontal irradiance;

## 3. ANN model description

ANN-based models are considered more appropriate in predicting the solar irradiance compared to the linear regression models. However, the accuracy of the ANN models is sensitive to the architecture of the neural networks. The process of selecting the optimum number of hidden neurons in an ANN model is still a challenge since it is normally based on the trial and error approach.

### 3.1 ANN architecture

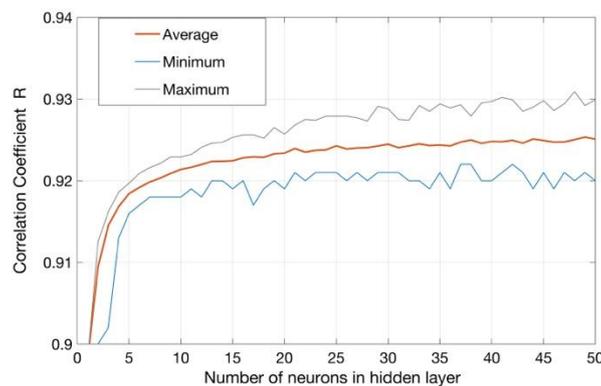
To evaluate the hourly global solar irradiance in terms of various climatic parameters, a 3-layer feed forward neural network with the default number of neurons in hidden layer and 1 output neuron was developed initially. For ANN training, the network architecture with Levenberg–Marquardt learning algorithm and hyperbolic tangent sigmoid transfer function was used in the developed model. The three years hourly data obtained from HKO was used for the ANN development. The proportions of the data for training, validation and test sets were 75%, 15% and 15%. The elements of three subsets were chosen randomly to guarantee the representativeness of all climate patterns. The input variables (predictors) to the ANN were the solar altitude and meteorological parameters, all the variables were normalized to the range of -1 to 1 before training. The target output was the hourly clearness index  $K_t$  (ratio of global horizontal irradiance to extraterrestrial horizontal irradiance) which is the most commonly used indicators in both global solar radiation models and direct/diffuse solar irradiance prediction models.

The most common approach of estimating  $K_t$  is to correlate it with other meteorological data used as predictors in simple regression equation. Table 2 summarizes all the predictors of hourly clearness index  $K_t$  for the ANN models. All variables were evolved in the initial neuron networks which consists of 10 input neurons and 1 output neuron. The crucial issue is how to determine the most appropriate number of neurons in the hidden layer. If the number of neurons is too small, the ANN may not capture the contributions of each predictor and if it is too large, the network has the tendency to overfit the data and requires more computations.

**Table 2.** Predictors of hourly clearness index  $K_t$  for ANN models.

Variable	Notation	Unit	Variable	Notation	Unit
Sine of solar altitude angle	$\sin(\alpha)$	-	Air temperature	$Temp$	$^{\circ}\text{C}$
Sunshine duration	$Sh$	hour	Wet bulb temperature	$Wet$	$^{\circ}\text{C}$
Cloud cover amount	$Cl_d$	octas	Dew-point temperature	$Dew$	$^{\circ}\text{C}$
Wind speed	$Spd$	m/s	Relative humidity	$Rh$	(%)
Visibility	$Vis$	km	Mean sea level air pressure	$Pre$	kPa

To find the optimum number of hidden neurons, the networks were built up with increasing number of hidden neurons from 2 to 50 to control the complexity of the neural network. Each proposed ANN configuration has been trained 50 times to stabilize the weight initialization process and delivered the best accuracy in the shortest processing time. The network performed well in terms of the root mean square error. To further evaluate the performance of each configuration, the R (correlation coefficient) of all datasets were examined during the process. Fig. 1 presents the average, minimum and maximum value of R for the networks which have been trained 50 times with the different number of hidden neurons. It can be found that the average value of R increases smoothly from 2 to 21 neurons in hidden layer and reaches 0.924 representing that the performance of the networks increases with the complexity of the networks. However, it decreases at 22 neurons, and after that, the R does not increase significantly. Thus, the optimum range of neurons was set to 20 to 40 for the ANN model and for the next analysis.



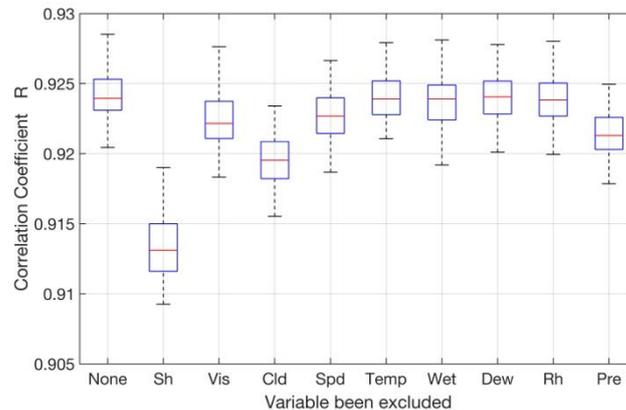
**Figure 1.** R values for different numbers of neurons in hidden layer

### 3.2 Sensitivity analysis of each parameter

To study the importance of each input variables on the predicted values of the target clearness index  $K_t$  and select appropriate predictors for the regression models, different configurations of the ANN model were established. To consider the effectiveness of individual predictors, models excluding (drop) one predictor from all the input variables were developed and the performance (R) of the corresponding neural network was examined. Each neural network was trained, validated and tested for 100 times with random number (20 to 40) of neurons in hidden layer following the results of the analysis of the optimum range of hidden neuron numbers.

The developed ANN with all the 10 predictors was found to give maximum R of 0.925 of predicted hourly global irradiance. When  $\sin(\alpha)$  was dropped from the networks, the R declined to 0.820 indicating the importance of  $\alpha$  for estimating global solar irradiance. The performance of other models with different parameters being dropped is shown in the boxplot in Fig. 2. As shown in the figure, the importance of each predictor can be identified by the descend range from the R value of models with all predictors. Except for the  $\sin(\alpha)$ , the most important predictors identified by the ANN models were sunshine duration ( $Sh$ ), amount of cloud cover ( $Cl_d$ ), mean sea level pressure ( $Pre$ ) and visibility ( $Vis$ ).

Among these predictors,  $Sh$  (expressed in fractions of an hour over a 60 min interval) shows the strongest correlation with GHI, and it is mostly used in empirical models for predicting monthly or daily average global solar irradiance. Through the sensitivity analysis, these important predictors were selected to examine the various correlations with  $K_t$  as used by other regression techniques. Several different combinations of these predictors were used in the regression analysis and the mathematical expressions of the clearness index  $K_t$  were given.



**Figure 2.** Performance of the neural networks when a single variable is excluded

#### 4. Regression and results

Although models developed using ML techniques tend to be more accurate, most of them are too complex and less interpretable which cannot be easily adopted by other users. What's more, some of the predictors of these models such as meteorological variables are not always available in rural areas where the measurements are limited by some conditions. However, the ML algorithm can be adopted to identify the contribution of individual input variables in the estimation of output (i.e.  $K_t$ ) as shown in Section 3. Thus, the relevant predictors identified by ANN models were selected to create empirical models by regression techniques. It should be emphasized that regression models represent a good statistical tool with both the simplicity and the flexibility to capture the relationship between  $K_t$  and various climate parameters. This section gives the mathematical expressions of the empirical models for predicting  $K_t$  with several different variable combinations.

To establish different empirical models, regressions were conducted with the different combination of 6 predictors namely solar altitude- $\sin(\alpha)$ , day number of a year- $n$ , sunshine duration- $Sh$ , amount of cloud cover- $Cld$ , mean sea level pressure- $Pre$  and visibility- $Vis$ . The  $\sin(\alpha)$  and  $n$  were used in all the equations since  $\alpha$  is always available at a specific location and  $n$  can reflect the seasonal fluctuations of GHI. The choice of suitable models under specific circumstance depends on the availability of these meteorological data and the accuracy of the models. The models developed by regression for estimating horizontal GHI with their coefficient of determination ( $R^2$ ) are shown in Eqs. (1) to (15). Polynomial or exponential expressions of the predictors are commonly used in modeling the equations, the differences are the number of input parameters and their combinations.

- **Model with 2 predictors:**

$$K_t = \exp[8.231 \sin(\alpha) - 7.479 \sin^2(\alpha) + 2.714 \sin^3(\alpha) - 0.001 \sin(n) - 0.226 \sin^2(n) - 0.416 \sin^3(n) - 4.095], R^2 = 0.485. \quad (1)$$

- **Models with 3 predictors:**

$$K_t = \sin(\alpha)[0.119 + 0.120 \sin(\alpha) - 0.061 \sin(n) + 0.889(Sh) - 0.467(Sh)^2] - 0.002, R^2 = 0.801. \quad (2)$$

$$K_t = \sin(\alpha)[0.507 + 0.218 \sin(\alpha) - 0.072 \sin(n) + 0.395 \left(\frac{Cld}{8}\right) - 0.909 \left(\frac{Cld}{8}\right)^2] - 0.011, R^2 = 0.736. \quad (3)$$

$$K_t = \sin(\alpha)[0.33 + 0.176 \sin(\alpha) - 0.137 \sin(n) + 0.028(Pre - 101.325) + 0.029(Pre - 101.325)^2] - 0.015, R^2 = 0.473. \quad (4)$$

$$K_t = \sin(\alpha)[0.596 - 0.054 \sin(\alpha) - 0.097 \sin(n) + 0.390 \left(\frac{Vis}{16.5} - 1\right) - 0.485 \left(\frac{Vis}{16.5} - 1\right)^2], R^2 = 0.542. \quad (5)$$

$$K_t = \sin(\alpha)[0.095 + 0.125 \sin(\alpha) - 0.059 \sin(n) + 1.698(Sh) - 2.801(Sh)^2 + 1.556(Sh)^3] - 0.0012, R^2 = 0.804. \quad (6)$$

- **Models with 4 predictors:**

$$K_t = \sin(\alpha)[0.210 + 0.224 \sin(\alpha) - 0.070 \sin(n) + 0.329(Sh) - 0.172 \left(\frac{Cld}{8}\right)] + 0.012, R^2 = 0.791. \quad (7)$$

$$K_t = \sin(\alpha)[0.074 + 0.198 \sin(\alpha) - 0.072 \sin(n) + 0.410(Sh) + 0.012(Pre - 101.325)] + 0.013, R^2 = 0.782. \quad (8)$$

$$K_t = \sin(\alpha)[0.122 + 0.104 \sin(\alpha) - 0.062 \sin(n) + 0.390(Sh) + 0.120 \left(\frac{Vis}{16.5} - 1\right)] - 0.005, R^2 = 0.789. \quad (9)$$

$$K_t = \sin(\alpha)[0.645 + 0.244 \sin(\alpha) - 0.084 \sin(n) - 0.568 \left(\frac{Cld}{8}\right) - 0.036(Pre - 101.325)] - 0.007, R^2 = 0.705. \quad (10)$$

$$K_t = \sin(\alpha)[0.565 + 0.171 \sin(\alpha) - 0.071 \sin(n) - 0.530 \left(\frac{Cld}{8}\right) + 0.279 \left(\frac{Vis}{16.5} - 1\right)] - 0.021, R^2 = 0.746. \quad (11)$$

$$K_t = \sin(\alpha)[0.288 + 0.170 \sin(\alpha) - 0.057 \sin(n) + 0.860(Sh) - 0.578(Sh)^2 - 0.052 \left(\frac{Cld}{8}\right) - 0.209 \left(\frac{Cld}{8}\right)^2] - 0.004, R^2 = 0.822. \quad (12)$$

• **Models with 5 predictors:**

$$K_t = \sin(\alpha)[0.062 + 0.16 \sin(\alpha) - 0.067 \sin(n) + 0.385(Sh) + 0.028(Pre - 101.325) + 0.0142 \left(\frac{Vis}{16.5} - 1\right)] + 0.005, R^2 = 0.791. \quad (13)$$

$$K_t = \sin(\alpha)[0.569 + 0.168 \sin(\alpha) - 0.071 \sin(n) - 0.531 \left(\frac{Cld}{8}\right) - 0.002(Pre - 101.325) + 0.278 \left(\frac{Vis}{16.5} - 1\right)] - 0.021, R^2 = 0.746. \quad (14)$$

• **Models with 6 predictors**

$$K_t = \sin(\alpha)[0.23 + 0.175 \sin(\alpha) - 0.063 \sin(n) + 0.285(Sh) - 0.205 \left(\frac{Cld}{8}\right) + 0.013(Pre - 101.325) + 0.165 \left(\frac{Vis}{16.5} - 1\right)], R^2 = 0.804. \quad (15)$$

The performance of each model can be evaluated by  $R^2$  between measurement values and predicted values. The  $R^2$ s are various based on the number of parameters and complexity of the models with the minimum value of 0.473 (Eq.4) and maximum value of 0.822 (Eq.12). As shown in Eq. (1), without any measured climate parameters,  $K_t$  can be roughly estimated by solar altitude although the performance of the model is relatively poor. When an additional predictor was added for modeling, there was a general rise in  $R^2$ . Specifically, the  $R^2$  increased significantly when  $Sh$  or  $Cld$  was included, while there was no increase or only slightly increase when  $Pre$  or  $Vis$  was added. The  $R^2$  of the model with only  $\sin(\alpha)$ ,  $n$  and  $Sh$  reached to 0.801. In this connection, Eq. (6) was created by adding the cubic  $Sh$  to the polynomial and the  $R^2$  increased to 0.804.  $Sh$  is a widely available climatic variable measured in many meteorological stations. Eq. (6) is a simple regression model that takes into consideration only  $Sh$  effects but still offers widespread applicability and good performance for predicting hourly GHI. When the number of predictors was increased to 4, 5 and 6, there was a general improvement of  $R^2$  comparing with those equations with 3 predictors. Eqs. (7) and (9) shown that the contribution of  $Cld$  and  $Vis$  to  $K_t$  is similar when they were added to  $Sh$  based model. Generally, when  $Sh$  is included in the models, the accuracy of these models tends to be higher than those with other predictors.

**Table 3.** Summary of the performance of regression models

Models	Input parameters	MBE (W/m <sup>2</sup> )	%MBE (%)	RMSE (W/m <sup>2</sup> )	%RMSE (%)	R <sup>2</sup>
Eq.1	$\sin(\alpha), n$	+11.04	+0.13	213.8	59.4	0.485
Eq.2	$\sin(\alpha), n, Sh$	+0.64	-1.73	127.5	35.4	0.801
Eq.3	$\sin(\alpha), n, Cld$	+2.35	-0.66	138.3	38.4	0.736
Eq.4	$\sin(\alpha), n, Pre$	+16.88	+0.63	214.3	59.5	0.473
Eq.5	$\sin(\alpha), n, Vis$	-68.05	-0.28	236.2	65.6	0.542
Eq.6	$\sin(\alpha), n, Sh$	+1.21	+0.3	124.5	34.6	0.804
Eq.7	$\sin(\alpha), n, Sh, Cld$	-0.36	-0.1	127.7	35.5	0.791
Eq.8	$\sin(\alpha), n, Sh, Pre$	+2.35	+0.7	133.5	37.1	0.782
Eq.9	$\sin(\alpha), n, Sh, Vis$	-54.15	-15.0	140.4	39.0	0.789
Eq.10	$\sin(\alpha), n, Cld, Pre$	-2.40	-0.7	150.4	41.8	0.705
Eq.11	$\sin(\alpha), n, Cld, Vis$	-129.7	-36.0	205.6	57.1	0.746
<b>Eq.12</b>	$\sin(\alpha), n, Sh, Cld$	<b>-1.65</b>	<b>-0.5</b>	<b>117.3</b>	<b>32.6</b>	<b>0.822</b>
Eq.13	$\sin(\alpha), n, Sh, Pre, Vis,$	-62.1	-17.2	144.9	40.2	0.791
Eq.14	$\sin(\alpha), n, Cld, Pre, Vis,$	-129.3	-35.9	205.2	57.0	0.746
Eq.15	$\sin(\alpha), n, Sh, Cld, Pre, Vis$	-76.4	-21.2	148.2	41.2	0.804

To further evaluate the performance of the developed empirical models, measured solar irradiance and climate data of 2015 was used to test the models. The performance indices in terms of MBE, %MBE, RMSE and %RMSE were calculated and the results are summarized in Table 3. It can be seen that most of the MBEs are negative which means the models mainly underestimate the GHI. The RMSEs were

basically smaller with the increase of  $R^2$ , the smallest and maximum value was found to be  $117.3\text{W/m}^2$  (32.6%) and  $236.2\text{W/m}^2$  (65.6%). In general, the performance of the regression models increases with the increase of the number of predictors and the complexity of the expressions. The increase of polynomial power could further enhance the performance of the models. Eq. (12) has the highest  $R^2$  and lowest RMSE when the quadratic expressions of  $Sh$  and  $Cld$  were used in the polynomial function. It indicates that  $Sh$  and  $Cld$  have the largest contribution to the estimation of hourly horizontal GHI. The findings will be helpful for users to select appropriate models according to the availability of measured parameters.

## 5. Conclusions

This study proposes an approach for estimating the horizontal global solar irradiance from meteorological parameters. Sensitivity analysis of individual parameters was conducted using ANN techniques and the importance of each predictor was identified. Four climate variables along with solar altitude and day number were selected to create the prediction models by regression techniques according to the results of sensitivity analysis. Hourly meteorological and solar irradiance data of Hong Kong between 2012 and 2015 were used for the analysis. The equations of various models with different combinations of predictors were given and their performance was tested by several indices. The estimation accuracy of the regression models depends on the number of predictors and the complexity of the mathematical expressions. More long-term measured data for different locations will be analyzed in the future work of this study, more combinations of the predictors and various forms of the equations should also be evaluated. Nonetheless, the empirical models developed by this study would be helpful for the estimation of hourly GHI when less meteorological data is available. The findings are important for solar energy system and energy efficient building designs.

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