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Estimation and Comparison of the Clearness Index using Mathematical Models - Case study in the United Arab Emirates

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Abstract: An accurate knowledge of the properties of solar radiation has a fundamental importance to study and to design solar energy systems. The clearness index plays a key factor in providing information about the transmitted solar radiation through the atmosphere compared to the extraterrestrial solar radiation. It plays a major role in understanding the meteorological phenomena, variations in the atmosphere, and sky conditions. However, the astronomical calculation requires a geographical consideration and precise measurement of the solar radiation. This study carried out an evaluation of the clearness index by applying mathematical approaches, a multiple linear regression function and a neural network approach, to the accumulated data of solar radiation, monthly temperature variation, humidity, and pressure of Dubai and Abu Dhabi meteorological stations in the United Arab Emirates.

Keywords: Global solar radiation; Extraterrestrial Solar Radiation; Meteorological parameters

1. Introduction

It is well known that the need to advance the use of green energy seeks to reduce environmental pollution, achieve economic goals, and undermine the mechanism of climate change. Solar radiation is considered as the cleanest, most accessible and alternative source of renewable energy that can meet future energy needs. With recent developments in solar energy projects around the globe, a proper estimation of solar radiation and related parameters is most needed[1-4].

To evaluate the solar energy potential and the feasibility of using solar energy in a certain country, we need to have the best estimation of solar potential. Various theoretical models are now in use for the most precise estimation of solar energy indicators[5-10]. Many meteorological parameters from the available data from weather stations, such as temperature, relative humidity, wind and pressure, are also commonly used to estimate the global solar radiation in a specific region[11-15]. Several studies are conducted to explore various models at different locations in the world, and many comparisons have been made to optimize and find the best model that can be used to estimate the clearness index and global solar radiation[16-18]. Such models used aggression analysis of different meteorological parameters, different locations, and different amount of data. United Arab Emirates is one of the countries that receives a lot of solar radiations in the region and in the world as a whole, and has taken several measures to empower and increase the use of renewable energy in the region. Therefore, accurate analytical studies of solar parameters are essential to quantify the use as a source of energy.

Clearness index is defined as the ratio of the global solar radiation and the extraterrestrial solar radiation, providing essential information about the atmospheric conditions for a specific location. Furthermore, the value of the clearness index is between 0 and 1, and it is at its maximum (= 1) if all radiations are able to pass through the atmosphere without reflection or deflection. It is given by the formula:

$$K = \frac{H}{H_0} \tag{1}$$

where H is the global solar radiation and H_0 is the extraterrestrial solar radiation. The clearness index can be estimated in the absence of observed values of a specific location, from other measured meteorological parameters. All the meteorological parameters have been discussed in details in reference[19]. Moreover, the clearness index has been modelled in many studies, for different locations around the globe, and using different mathematical modelling methods[16), 20-28)].

At the top of the atmosphere, the horizontal daily solar radiation can be calculated as:

$$Q_0 = 4I_0/\pi\,[cos(\varphi).cos(\delta).cos(\omega) + \omega.sin(\varphi).sin(\delta)], \quad (2)$$

where Q_0 is the horizontal extraterrestrial solar radiation, I_0 is the extraterrestrial, φ is the latitude of the station, δ is the declination angle, and ω is the sunrise hour angle. These variables are given in the following equations:

$$I_0 = I_{sc}[1 + 0.033\cos(360d/365)], \quad (3)$$

with $I_{sc} = 1370$ W/m2 is defined as the solar constant.

$$\delta = 24.45\sin[360\,(248 + d)/365], \quad (4)$$

$$\omega = cos^{-1}[-\tan(\varphi)\tan(\delta)], \quad (5)$$

Analytical models for estimating the monthly clearness index are analyzed in this paper using the available meteorological data for various parameters, such as humidity, temperature variation and pressure. The investigated data is obtained from two stations in United Arab Emirates, namely Dubai and Abu Dhabi. The rest of the paper is organized as follows: Section 2 presents an overview of the data, the details of the modelling methods, and the statistical evaluation of the method. In section 3, results of the comparison between theoretical models and real data is discussed. Finally, the summary and conclusions are given in section 4.

2. Materials and methods

2.1 DATA:

In this work, meteorological data of humidity, average temperature, and pressure were provided by the National Center of Meteorology in the United Arab Emirates NCM[29)]. Two stations are included in the study, Dubai (25° 15' 10" N, 55° 21' 52" E) and Abu Dhabi (24° 28' 38" N, $54° 19' 40" E). The available data is provided for a period of 10 years, staring from 2010 to 2019. We would like to point out that few other stations are in use by the National Center of Meteorology, as seen in Figure 1, however, we chose to use Dubai and Abu Dhabi stations because they present the two largest cities between the seven emirates of the United Arab Emirates. The geographical information and the monthly average values of each climate parameter are summarized in Table. 1 and Table. 2, and presented in Figure 2 for both Dubai and Abu Dhabi stations.

Fig. 1: Red circles indicate the locations of the weather stations in Dubai as shown in the NCM map.

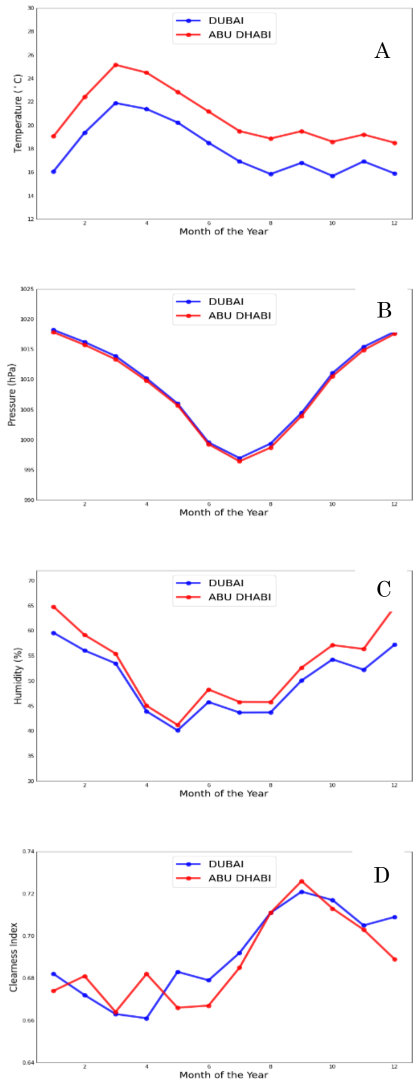

Fig. 2: The monthly variation of the meteorological parameters of this study in Dubai and Abu Dhabi stations and for 10 years of data. Monthly average data is presented in the X-axis. The presented parameters are the temperature variation (a), pressure (b), humidity (c) and the clearness index for both stations (d)

The four meteorological parameters, used in this study, are presented in Figure 2 for both Dubai and Abu Dhabi stations. The difference between day and night temperature is much larger in the winter and spring seasons than in the summer and autumn seasons.

Therefore, the peak value of the temperature variation is observed in March for both stations, and the minimum value is in October. On the other hand, the pressure and relative humidity parameters, shown in Figure 2b and 2c, respectively, are inversely proportional to the temperature. Figure 2d shows the average clearness index over the ten years of selected data. It is observed that the clearness index varies from 0.661 to 0.721 and 0.664 to \$0.726\$ for Dubai and Abu Dhabi sites, respectively. The highest values for both sites are observed in September while the lowest values are observed in April and March, respectively. The weather conditions, geographical site, and measured meteorological parameters could cause such a variation in the measured clearness index.

2.2 Modeling the clearness index

Considering the available meteorological parameters, some theoretical models may be developed to estimate the clearness index. Mathematical models are presented using an empirical model and a neural network approach.

2.2.1 Empirical model:

The estimation of the clearness index from meteorological data has been triggered and widely presented by scientists around the globe for different locations using different methods[19]. In regression studies, a model is developed to relate multiple parameters to a dependent variable. In the current approach, a regression analysis uses the three available independent parameters, humidity (H), temperature variation ($\Delta T = T_{max} - T_{min}$) and pressure ($P$), to estimate the clearness index of both Dubai and Abu Dhabi stations. The clearness index is represented by a multiple linear regression model (MLRM) as:

$$K = a + b\Delta T + cH + dP, \quad (6)$$

where a, b, c, and d, are the empirical coefficients.

2.2.2 Neural network approach (NN)

Machine learning is a commonly used subject in data analysis and artificial intelligence. A neural network is a programming paradigm that consists of a multilayer network of neurons[30]. Such networks are used to find patterns and algorithms on a large number of datasets with many input variables. Neural networks are constructed with a number of inputs and layers, one output layer, and a number of hidden layers that process the correlation between variables. The Neural Network approach has been already applied by different scientists to perform meteorological studies at different sites around the globe. Saeid, Omaid, and Ahmad[31] have used this approach to predict the clearness index using various meteorological parameters. They used 30 years of monthly collected data in 19 sites in Iran. Furthermore, the Neural Network method is widely used to estimate the direct solar radiation[32-33]. The neural network presented in this analysis is a forward multilayer perception implemented in the ROOT software[34]. It uses the meteorological parameters, temperature variation, humidity, and pressure, of the Dubai and Abu Dhabi stations as inputs and calculates the clearness index as an output of the network, as shown in the diagram in Figure 3.

Table. 1: The monthly variation of the meteorological parameters of this study in Dubai stations and for 10 years of data. The presented parameters are the temperature variation, pressure, humidity, and the clearness index for both stations.

Station	DUBAI Latitude: 25° 15′ 10″ N Longitude: 55° 21′ 52″ N			
parameter / Month	K	ΔT (°C)	H (%)	P (hPa)
Jan.	0.682	16.07	59.58	1018.21
Feb.	0.672	19.36	56.05	1016.21
Mar.	0.663	21.9	53.49	1013.88
Apr.	0.661	21.39	43.92	1010.19
May	0.683	20.24	40.11	1006
June	0.679	18.51	45.78	999.55
Jul.	0.692	16.92	43.67	996.96
Aug.	0.711	15.84	43.71	999.37
Sep.	0.721	16.8	50.07	1004.47
Oct.	0.717	15.68	54.28	1011.06
Nov.	0.705	16.92	52.22	1015.41
Dec.	0.719	15.89	57.2	1017.92

Table. 2: The monthly variation of the meteorological parameters of this study in Abu Dhabi stations and for 10 years of data. The presented parameters are the temperature variation, pressure, humidity, and the clearness index for both stations.

Station	DUBAI Latitude: 25° 15′ 10″ N Longitude: 55° 21′ 52″ N			
parameter / Month	K	ΔT (°C)	H (%)	P (hPa)
Jan.	0.682	16.07	59.58	1018.21
Feb.	0.672	19.36	56.05	1016.21
Mar.	0.663	21.9	53.49	1013.88
Apr.	0.661	21.39	43.92	1010.19
May.	0.683	20.24	40.11	1006
June	0.679	18.51	45.78	999.55
Jul.	0.692	16.92	43.67	996.96
Aug.	0.711	15.84	43.71	999.37

Sep.	0.721	16.8	50.07	1004.47
Oct.	0.717	15.68	54.28	1011.06
Nov.	0.705	16.92	52.22	1015.41
Dec.	0.719	15.89	57.2	1017.92

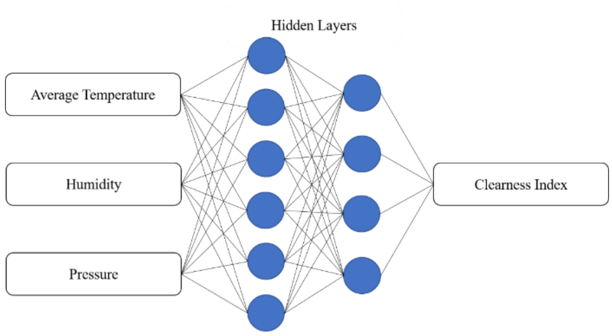

Fig. 3: The structure of the neural network used in the analysis.

Table. 3: The clearness index values from original data and the estimated values from the MLRM, and NN methods.

	DUBAI			ABU DHABI		
Month	Data	MLRM	NN	Data	MLRM	NN
Jan.	0.682	0.674	0.679	0.677	0.661	0.664
Feb	0.671	0.681	0.671	0.659	0.653	0.655
Mar	0.663	0.664	0.662	0.665	0.663	0.661
Apr	0.661	0.682	0.660	0.658	0.671	0.678
May	0.683	0.666	0.680	0.675	0.682	0.690
Jun	0.679	0.667	0.671	0.672	0.672	0.692
Jul	0.692	0.685	0.685	0.701	0.674	0.698
Aug	0.711	0.711	0.715	0.659	0.695	0.703
Sep	0.721	0.726	0.25	0.717	0.697	0.704
Oct	0.717	0.713	0.720	0.705	0.689	0.669
Nov	0.705	0.703	0.702	0.696	0.685	0.692
Dec	0.719	0.689	0.699	0.691	0.691	0.696

2.2.3 Statistical evaluation method

The performances of the estimated values from each model and the measured values were assessed using fundamental error method that has been used to assess the accuracy of solar energy studies[16-35]. The statistical indicators used to evaluate the reliability of the models are calculated using the following schemes:

$$R^2 = 1 - \left\{\frac{\sum_{i=1}^{N}(K_{im} - K_{ie})^2}{\sum_{i=1}^{N}(K_{im} - K_{avg,m})^2}\right\}, \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(K_{ie} - K_{im})^2}{N}} \quad (4)$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(K_{ie} - K_{im}), \quad (5)$$

$$PE = \frac{1}{N}\sum_{i=1}^{N}\frac{K_{im} - K_{ie}}{K_{im}} \times 100, \quad (6)$$

where K_{ie}, K_{im}, and $K_{avg,m}$ are the i^{th} estimated, measured, and average measured values, respectively, and N is the total number of observations. The *RMSE* indicates the deviation between the estimated and measured values. *MBE* and *MPE* indicate the tendency of the model to under or overestimate of the estimated values.

Table. 4: Statistical evaluation coefficients of the empirical and Neural network models for Dubai and Abu Dhabi stations.

	Model	R^2	RMSE	MBE E-2	MPE
Abu Dhabi	MLRM	0.893	0.262	-0.177	0.171
	NN	0.871	0.251	0.273	0.233
Dubai	MLRM	0.866	0.239	-0.314	0.166
	NN	0.862	0.208	0.221	0.352

3. Results and Discussion

Average monthly meteorological data of Dubai and Abu Dhabi stations were evaluated between the years of 2009 and 2019. The value of the clearness index can have a low or high value (between 0 and 1). This depends on the solar radiation, atmospheric conditions, and the location. Figure 4 and Figure 5 show a comparison of the clearness index from the original dataset and results of the NN and MLRM methods, presented in Table. 3, fitted with quantic polynomial, for Dubai and Abu Dhabi stations, respectively. Both models can describe the original value with a good agreement. The lowest values from the MLRM and NN distributions for Dubai station are obtained in April (K_{MLRM}= 0.658, K_{NN}= 0.66), and the highest values are obtained in September (K_{MLRM} = 0.717, K_{NN} = 0.725). The lowest values from the *MLRM* and *NN* distributions for Abu Dhabi station are obtained in February (K_{MLRM} = 0.653, K_{NN} = 0.655), and the highest values are obtained in September (K_{MLRM} = 0.697, K_{NN} = 0.704). This is consistent with the lowest and measured values (K_{Dubai} = 0.661 in April, $K_{Abu\ Dhabi}$ = 0.664 in March) and highest measured values (K_{Duba} = 0.721 in September, $K_{Abu\ Dhabi}$ = 0.726$ in September). It is expected that the global solar radiation reaches the peak in the summer period (May through September) and to be at minimum in the winter (December through February). Therefore, the clearness index is also expected to reach the maximum during the summer and to be at the minimum in the winter. However, the peak is observed in September while the lowest value is in April for Dubai station and in March for Abu Dhabi station. These variations in the clearness index values can be explained by the seasonal fluctuations across the year, with patterns comparatively higher throughout the summer months. The lower panels in Figure 4 and Figure 5 show the radio of the results from the applied models to the real data. In principle, the closer the model-data ratio to unity, the more accurate the obtained values. It can be clearly seen that the obtained ratios are close to unity over the entire range.

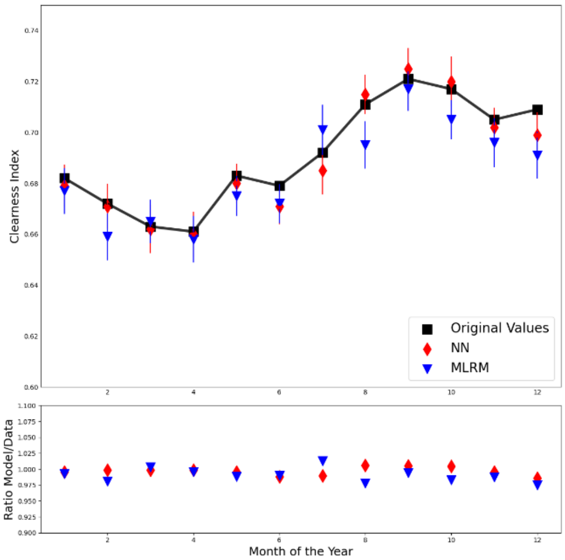

Fig. 4: A comparison between the observed clearness index and the estimated clearness index for Dubai station. Results are presented using the MLRM and NN models for Dubai station. The lower panel shows the ration between the results of the models and real data.

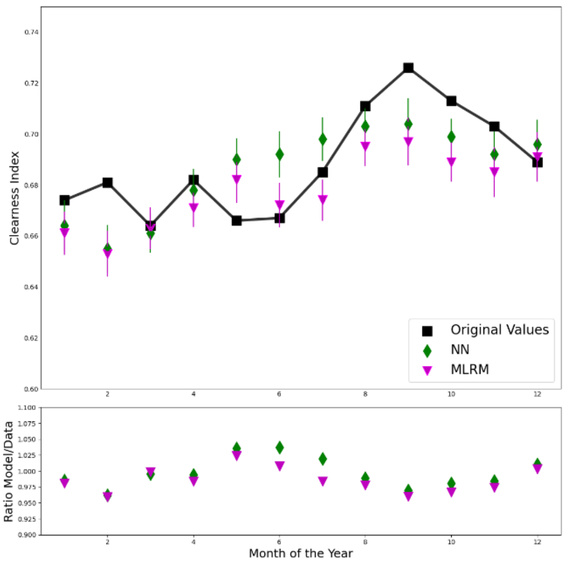

Fig. 5: A comparison between the observed clearness index and the estimated clearness index for Abu Dhabi station. Results are presented using the MLRM and NN models for Abu Dhabi station. The lower panel shows the ration between the results of the models and real data.

To evaluate the performance of the applied algorithms, statistical indicators were used, namely R^2, *RMSE, MBE*, and *MPE* (Equations .3, 4, 5, and 6) using ROOT[34]. The derived statistical parameters of the *MLRM* and *NN* models for both stations are shown in Table. 4. The average value of R^2 is 0.88 for the empirical model and 0.867 for the neural network model, which reflects a good performance of the used models. An insignificant underestimation is observed in the *MBE* of the empirical model, while a small overestimation is seen for the neural network models. Nevertheless, the comparison of the estimated and measured values of the clearness indexes are in good agreement, with a smaller deviation for Dubai than Abu Dhabi station.

4. Summary and Conclusions

In this paper, the clearness index was obtained for two meteorological stations in United Arab Emirates, Dubai and Abu Dhabi. The values of the temperature variation, humidity and pressure, and clearness index were used over a period of 10 years. Two mathematical models were developed for the estimation of the clearness index. The performance of the applied models was evaluated in terms of the statistical indicators R_2, *RMSE, MBE*, and *MPE*. Table 3 summarized the model evaluation results. The comparison between the estimated and measured values of the clearness index agrees with a coefficient of determination within the range from 0.862 - 0.893. It can be concluded that both the empirical and neural network approaches can be employed to estimate the clearness index. However, a better description was obtained for Dubai station.

There is no reason to doubt the possibility of estimating the clearness index using mathematical models. However, this research can be extended to include data from more meteorological parameters and stations. Additionally, including daily data and over a longer period of time will result in a better accuracy in estimating the clearness index. Future research will focus on including more meteorological parameters, extra stations, larger set of data, and additional analytical tool based on copula distributions.

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Nomenclature

K	Clearness Index
H	Global Solar Radiation
H_0	Extraterrestrial Solar Radiation
NCM	National Center of Meteorology
NLRM	Multiple Linear Regression Model
NN	Neural Network
ΔT	Temperature Variation
P	Pressure
H	Humidity

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