

A Review of Regression Models Employed for Predicting Diffuse Solar Radiation in North-Western Africa

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The knowledge of diffuse solar radiation (H_d) is of almost importance for determining the gross primary productivity, net ecosystem, exchange of carbon dioxide, light use efficiency and changing colour of the sky. However, routine measurement of H_d is not available in most locations in North-Western Africa. During the past 36 years in order to predict H_d in the horizontal surface on hourly, daily and monthly mean basis, several regression models have been developed for numerous locations in North-Western Africa. As a result, several input parameters have been utilized and different functional forms applied. The regression models so far utilized were classified into six main categories and presented based on the input parameters applied. The models were further reclassified into numerous main groups and finally represented according to their developing year. In general, 188 regression models, 33 functional forms and 20 groups were reported in literature for predicting H_d in North-Western Africa. The regression and soft computing models developed within North-Western Africa and across the globe were examined in order to determine the best technique of prediction. The result revealed that soft computing models are more suitable for predicting H_d in North-Western Africa and across the globe.

Keywords: Diffuse solar radiation; Regression models; Classification; Functional forms; North-Western Africa

1. Introduction

As a result of exponentially increasing costs of fossils, uncertainty of availability and transportation, environmental pollution, and general awareness amongst common people, the renewable sources which are environmental friendly since they have much lower environmental impact compared to conventional sources have enabled smart energy to gain more attention from researchers, governments, non-governmental organisations (NGOs) and industries etc. in recent years due to the rapid growth of the global energy demands. Solar energy in the form of radiation received at the surface of the earth is the most preferred sustainable source of renewable energy in the form of solar photovoltaic, solar thermal. Other sources of renewable energy are wind, biomass, small and big hydro, tidal, wave, ocean etc. as a result of their inexhaustible nature and abundant availability globally. These attributes make solar energy to be accepted worldwide as a key energy

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source for the future with respect to the environmental issues associated with fossils as well as their limited reserves. Therefore, solar energy is the best substitute of fossils owing to the ever growing demand for energy globally. In fact, about 40 GW of solar photovoltaics (PV) capacity was installed in 2014 and the International Energy Agency, IEA [1] predicts that by 2050, photovoltaic (PV) as a renewable energy source (solar energy) may become one of the most promising sources of energy that will provide about 11% of global electricity production and would reduce 2.3 gigatonnes of CO₂ emissions per year. As a result, more and more penetration of solar energy technologies to the worlds' energy sector is indeed appealing for supplying a notable part of the electricity, heating, cooling, cooking, and drying of all types of things: clothes, agricultural produce, cash crops, and bricks etc. Therefore, a good working knowledge of available solar energy obtained principally from global solar radiation with its diffuse and direct components in a particular location are of great importance in designing and sizing of solar energy conversion systems.

Diffuse solar radiation is the component of global solar radiation reaching the earth's surface after having been scattered from the direct horizontal irradiation by molecules, aerosols or suspended particular matter such as black carbon, organic carbon, dust and sea salt in the atmosphere. Diffuse solar radiation plays an important role in determining the gross primary productivity, net ecosystem exchange of carbon dioxide, light use efficiency, changing colour of the sky and baseline for estimating and understanding diffuse solar radiation parameters such as diffuse solar radiation and global solar radiation on surfaces, diffuse photosynthetically active radiation etc. Moreover, solar energy among other sources of renewable energy has remained the most viable source of energy that has the capacity to sustain and maintain all the activities and processes that support life of animals, supply heat to the atmosphere and lands, generate its wind, drive the water cycle, warm the ocean and support life of plants.

The accurate determination and clear understanding of the diffuse solar radiation parameters is required for many applications such as energy management, solar energy, light studies, architectural research, hydrological process and biometeorology, crop production, remote sensing of vegetable and carbon cycle modelling, designing and sizing photovoltaic systems, development of thermal and electrical solar energy devices [2-6].

Diffuse solar radiation arises as a result of the interaction between the solar radiation incident on the top of the earth's atmosphere and the matter within it. Thus, understanding how this radiometric flux interacts with the matter within it and relates with its immediate environment thereby influencing diffuse light availability for energy, sky colour, agricultural, material and technological production and utilization for man's need is of utmost importance for modelling and estimating diffuse solar radiation in a particular geographical environment.

Diffuse solar radiation varies from one geographical location to another. It is a function of meteorological parameters such as evaporation, effects of cloudiness, relative humidity, precipitation, temperature, sunshine duration, extraterrestrial solar radiation, and reflection of the environs; geographical parameters such as latitude, longitude and elevation of the site; geometrical factors such as azimuth angle, sun azimuth angle; astronomical parameters like solar constant, earth-sun distance, solar declination and hour angle; physical parameters such as scattering air molecules, water vapour content, scattering of dust and other atmospheric constituents like O₂, N₂, CO₂, and O.

Measurement of diffuse solar radiation is often performed in many parts of the world by mounting a pyranometer on the axis of the ring on a roof top so as to receive only diffuse solar radiation and the ring is normally adjusted regularly to ensure that the direct

irradiance does not reach the pyranometer. As a result of cost of measuring equipment, its maintenance and calibration requirements, in rural and developing countries in Africa and several places around the world, several empirical models had been developed in Africa and other locations across the globe that can produce diffuse solar radiation data without the substantial cost of the instrumentation network that would otherwise be needed [7-10].

The most primitive model for estimating diffuse solar radiation was developed by Liu and Jordan [11]. These solar energy researchers correlated diffuse fraction (H_d/H) with clearness index (k_t). Their investigation has been adopted by numerous solar energy researchers in Nigeria and Egypt and across the globe as a baseline further developing regression models for estimating diffuse solar radiation using the same parameter, other meteorological parameters, geographical parameters, geometrical parameters and astronomical parameters that will best fit the local climate of their study.

However, diffuse solar radiation and other components of solar radiation such as direct normal irradiance, photosynthetically active radiation, evapotranspiration etc. have been predicted employing different soft computing techniques in recent times. This constitutes a widely accepted technique offering an alternative way to synthesize complex problems associated with solar energy prediction. These problems include inability to handle non-linear relationships in data; applying only calculable atmospheric, meteorological, astronomical, geographical, geometrical parameters such as extraterrestrial solar radiation, latitude, altitude, longitude, maximum sunshine duration, azimuth angle, solar declination, cosine of solar zenith angle, and hour angle. The soft computing technique has the capacity of accepting many input parameters for a particular model which is not possible applying regression technique and this strengthens its reliability. Therefore, applying soft computing techniques compared to regression techniques according to previous studies offers greater accuracy with prediction error in a range (less than 20 %) and could be very good in terms of diffuse solar radiation prediction as more and more soft computing approaches are demanded in the domains of renewable energy resource prediction [12-21].

Therefore, the main purpose of the study was to review regression models fitted in literature for predicting diffuse solar radiation in North-Western Africa and its objectives are identifying several input parameters and functional forms ever applied for predicting diffuse solar radiation in North-Western Africa; classify the regression models commonly employed in this part of Africa according to the main input parameters; compare the performance of regression and soft computing models applied and decide the best technique that can yield high accuracies of estimation for future purposes and finally identify the research gap.

2. Basic Parameters

The principal parameter of sunshine duration fraction, daily extraterrestrial radiation on the horizontal surface is significant for the prediction of diffuse solar radiation. Sunshine duration fraction is the ratio of actual sunshine duration to maximum possible sunshine duration expressed theoretically as:

$$S_o = \frac{2}{15} \cos^{-1}[-\tan \delta \tan \phi] \quad (1)$$

$$\delta = 23.45 \sin \left[\frac{360(n + 284)}{365} \right] \quad (2)$$

Where ϕ is the latitude, δ is the solar declination given by Yaniktepe and Genc [22] and n is the number of days of the year starting from first January. The daily extraterrestrial solar radiation is the solar radiation intercepted by horizontal surface during a day without the atmosphere and hourly extraterrestrial radiation has similar definition.

Hourly extraterrestrial solar radiation on the horizontal surface is given by Zhang *et al.* [23] as:

$$I_o = \frac{12 \times 3600 \times I_{SC}}{\pi} \left(1 + 0.033 \cos \frac{360n}{365} \right) \times \left(\cos \phi \cos \delta (\sin \omega_2 - \sin \omega_1) \sin \omega_S + \frac{\pi(\omega_2 - \omega_1)}{180} \sin \phi \sin \delta \right) \quad (3)$$

While the daily extraterrestrial solar radiation on the horizontal surface is given by Yaniktepe and Genc [23] as:

$$H_o = \frac{24}{\pi} I_{SC} \left(1 + 0.033 \cos \frac{360n}{365} \right) \times \left(\cos \phi \cos \delta \sin \omega_S + \frac{2\pi\omega_S}{360} \sin \phi \sin \delta \right) \quad (4)$$

Where the mean sunrise hour angle (ω_s) can be evaluated as:

$$\omega_s = \cos^{-1} [-\tan \delta \tan \phi] \quad (5)$$

I_{sc} is the solar constant, ω_1 and ω_2 are the limit hour angle of an hour, in which ω_2 is the larger, all in degrees and other symbols retain their usual meaning.

3. Evaluation Metrics

Evaluation, principally compares how well the observed and predicted fit each other. This evaluation is applied at numerous steps of the computing model development as for instance during the evaluation of the prediction model itself (during the training of a statistical model for instance), for judging the improvement of the computing model after some modifications and for comparing numerous computing models. As previously mentioned, this performance comparison is not easy for numerous reasons such as different predicted time horizons, numerous time scales of the predicted data and variability of the meteorological conditions from one site to another one. It works by comparing the predicted outputs \hat{y} with observed data y which are also measured data themselves linked to an error (or precision) of a measure.

Graphic tools are available for predicting the adequacy of the computing model with the experimental measurements via:

1. Time series of predicted diffuse solar radiation in comparison with measured diffuse solar radiation which allows visualizing easily the estimation quality. In Fig. 1a, for instance, high estimate accuracy in clear-sky conditions and a low one in partly cloudy conditions can be seen.
2. Scatter plots of estimated over measured diffuse solar radiation (as shown in Fig. 1b) which can reveal systematic bias and deviations depending on the diffuse solar radiation conditions and show the range of deviations that are related to the estimates.
3. Receiver Operating Characteristic (ROC) curves which compare the rates of true positives and false positive.

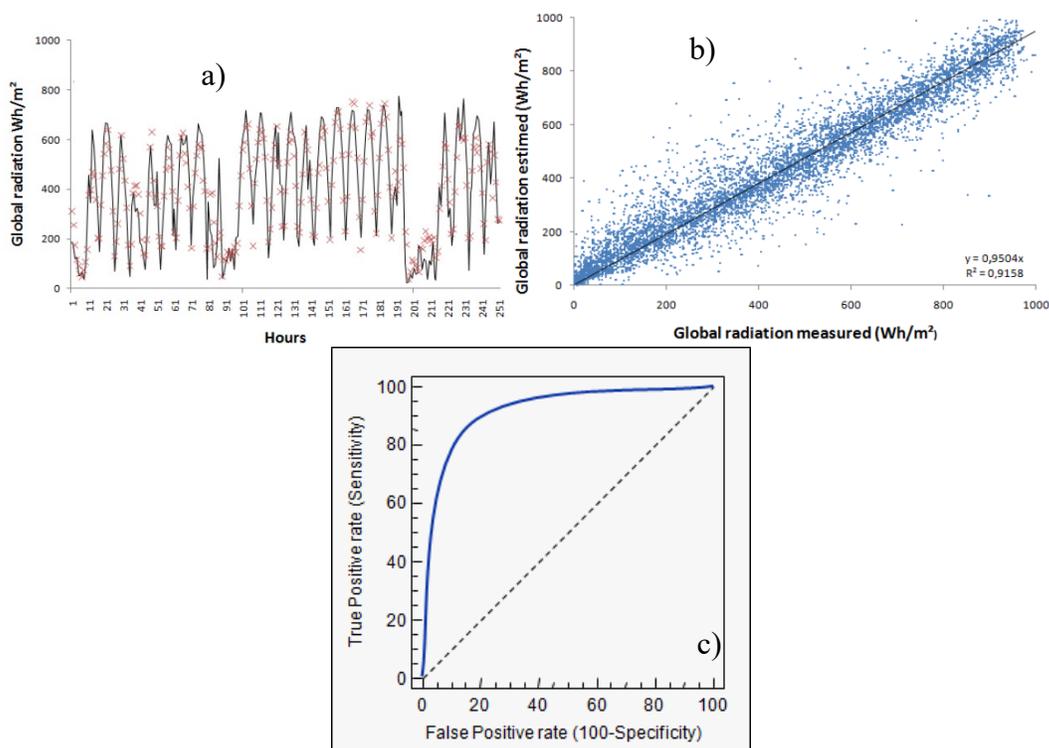


Fig. 1. a) Time series of predicted and measured global radiation for 2008 in Ajaccio (France); b) Scatter plot of predicted vs. measured global radiation in Ajaccio (France); c) Example of ROC curve (an ideal ROC curve is near the upper left corner).

Up till now, there is no standard evaluation measures accepted for diffuse solar radiation measurement, which makes the comparison of the estimating methods difficult. Sperati *et al.* [24] presented a benchmarking exercise within the framework of the European Actions Weather Intelligence for Renewable Energies (WIRE) with the purpose of evaluating the performance of state of the art computing models for short term renewable energy prediction or forecasting. This research is a very good example of reliability parameter utilization. They concluded that: “More work using more test cases, data and computing models needs to be performed in order to achieve a universal overview of all possible conditions. They also pointed out that test cases located all over Europe, the US and other relevant countries should be considered, in an effort to represent most of the possible meteorological conditions”. This study therefore illustrates very well the difficulties of performance comparisons encountered for diffuse solar radiation prediction. The commonly applied statistics for diffuse solar radiation prediction include the following: The Mean Bias Error (MBE) represents the mean bias of the prediction:

$$MBE = \frac{1}{N} \times \sum_{i=1}^N (\hat{y}(i) - y(i)) \quad (6)$$

\hat{y} is the predicted diffuse solar radiation, y the measured diffuse solar radiation and N the number of observations. The prediction will under-estimate or over-estimate the observations. Thus, MBE is not a good statistical indicator for the reliability of a computing model because the errors compensate each other but it allows seeing how much it overestimates or underestimates.

The Mean Absolute Error (MAE) is appropriate for comparing diffuse solar radiation estimation with linear cost functions, *i.e.*, where the costs resulting from a poor prediction are proportional to the estimation error:

$$MAE = \frac{1}{N} \times \sum_{i=1}^N |\hat{y}(i) - y(i)| \quad (7)$$

The mean square error (MSE) applies the squared of the difference between observed and estimated data. This statistical indicator penalizes the highest gaps:

$$MSE = \frac{1}{N} \times \sum_{i=1}^N (\hat{y}(i) - y(i))^2 \quad (8)$$

MSE is principally the statistical parameter which is minimized by the training algorithm.

The Root Mean Square Error (RMSE) is more sensitive to big prediction errors, and thus is good for applications where small errors are more tolerable and larger errors cause disproportionately high costs, as in the case of utility applications (http://www.cost.eu/about_cost). It is probably the reliability parameter that is most appreciated and employed:

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{N} \times \sum_{i=1}^N (\hat{y}(i) - y(i))^2} \quad (9)$$

The Mean Absolute Percentage Error (MAPE) is close to the MAE but each gap between observed and predicted value is divided by the observed value so as to consider the relative gap.

$$MAPE = \frac{1}{N} \times \sum_{i=1}^N \left| \frac{\hat{y}(i) - y(i)}{y(i)} \right| \quad (10)$$

This statistical indicator has a challenge that it is unstable when $y(i)$ is near zero and it cannot be defined for $y(i)=0$.

Of recent, these errors are normalized particularly for the RMSE; as reference the mean value of global radiation is generally employed but other definitions can be applied:

$$nRMSE = \frac{\sqrt{\frac{1}{N} \times \sum_{i=1}^N (\hat{y}(i) - y(i))^2}}{\bar{y}} \quad (11)$$

With \bar{y} is the mean value of y . Other statistical indicators exist and can be employed as the correlation coefficient (R), coefficient of determination (R^2), or the index of agreement (d) which is normalized between 0 and 1.

As the prediction accuracy strongly depends on the location and time period applied for evaluation and on other parameters, it is difficult to evaluate the quality of estimation from accuracy metrics alone. Then, it is best to compare the accuracy of different estimations against a common set of test data Pelland *et al.* [25]. “Trivial” prediction approach can be applied as a reference [26], the most common one is the persistence model (“things stay the same”, Trapero *et al.*, 2015) where the prediction is always equal to the last known data point. The diffuse solar radiation has a deterministic component due to the geometrical path of the sun. This characteristic may be included as a constraint to the simplest form of persistence in considering as an example, the measured data of the previous day or the previous hour at the same time as a prediction value. Other common reference forecasts include those based on climate constants and simple autoregressive methods. Such comparison with referenced NWP computing model is shown in Fig. 2. Generally, after 1 hour the forecast is better than persistence. For forecast horizons of more

than two days, climate averages show lower errors and should be preferred for diffuse solar radiation prediction.

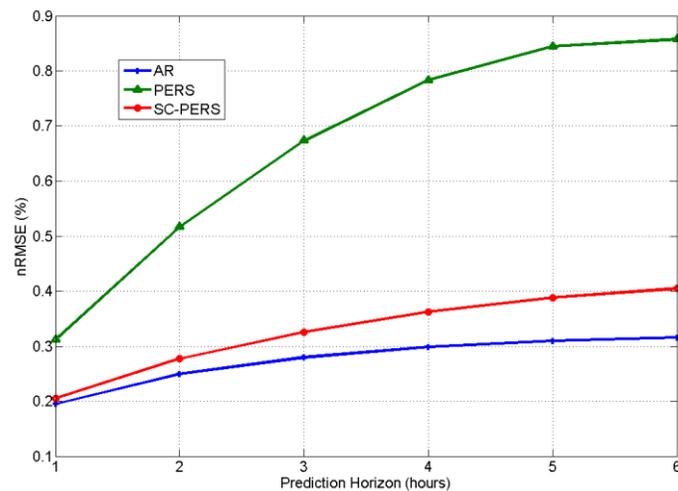


Fig. 2. Relative RMSE of forecasts (persistence, auto regression, and scaled persistence) and of reference models depending on the forecast horizon Lauret *et al.* [27].

Classically, a comparison of performance is performed with a reference computing model and to do it, a skill factor is employed. The skill factor or skill score defines the difference between the forecast and the reference forecast normalized by the difference between a perfect and the reference forecast Lauret *et al.* [27]:

$$\text{SkillScore} = \frac{\text{Metric}_{\text{forecasted}} - \text{Metric}_{\text{reference}}}{\text{Metric}_{\text{perfectforecast}} - \text{Metric}_{\text{reference}}} = 1 - \frac{\text{MSE}_{\text{forecastd}}}{\text{MSE}_{\text{reference}}} \quad (12)$$

Its value thus ranges between 1 (perfect forecast) and 0 (reference forecast). A negative value indicates a performance which is even worse compared to the reference (observed data). Skill scores can be adopted not only for comparison between observed and predicted diffuse solar radiation values but also for inter-comparisons of different diffuse solar radiation prediction techniques.

4. Regression Models

A regression model relates diffuse solar radiation (H_d) with other easily measurable parameters such as clearness index, mean daily extraterrestrial solar radiation, sunshine fraction and cloud cover by applying concise mathematical functions. As a result of its simplicity and high operability, the regression model is much more convenient for engineering applications.

Several regression models have been reported in literature for prediction H_d on the horizontal surface either on hourly mean basis (HB) or daily mean basis (DB) or monthly mean daily basis (MB) in Nigeria and Egypt. In this review, the H_d models are classified according to the basis of their input parameters applied in correlating with either diffuse fraction (H_d/H) or diffuse coefficient (H_d/H_o).

It has been accepted that H_d is relatively affected by meteorological parameters, astronomical factors, geographical factors, and geometrical factors [7, 9, 28-29]. This could be attributed to the uniqueness of local climate in determining the meteorological and

atmospheric parameters that best fit that particular locality. This also depends on the availability of input meteorological/atmospheric parameter(s) that a given radiometric station or an individual is capable of measuring routinely which finally turns out to be the best input parameter at the disposal of the researcher for predicting H_d in that location factors [7, 9]. Thus, in North-Western Africa, the models for predicting H_d can be classified into six (6) following categories based on the employed meteorological and atmospheric parameters via:

1. Clearness index-based models
2. Sunshine-based models
3. Cloud-based models
4. Extraterrestrial Solar Radiation-based models
5. Monthly-based models
6. Hybrid Parameter-based models

4.1 Clearness Index-Based Models

The clearness index (k_t) indicates the percentage depletion by the sky of the incoming solar radiation and therefore gives both the level of availability of solar radiation and changes in the atmospheric condition in a given environment [8, 30-32]. Mathematically, clearness index is the ratio of horizontal global solar radiation to the extraterrestrial solar radiation (H_o) on daily or monthly basis as found in literature expressed as:

$$k_t = \frac{H}{H_o} \quad (13)$$

For this reason, clearness index is closely related to H_d , hence, it has been known as a determinant parameter for estimation of H_d . One of the greatest characteristics of the models from this class is their convenient application, since for utilizing them only measured H data is needed. Numerous functional forms (exponential form, logistic form, logarithm form, second order, third order and power form) have been applied for estimating HB, DB and MB diffuse horizontal irradiation in literature are introduced according to their developing year under this section.

4.1.1 Group 1

Empirical models from this group are parameterized as the first-order polynomial function of the clearness index according to their functional forms and developing year. The functional forms are as follows:

$$\frac{H_d}{H_o} = a + b \left(\frac{H}{H_o} \right) \quad (14)$$

$$\frac{H_d}{H} = a + b \left(\frac{H}{H_o} \right) \quad (15)$$

$$\frac{H_d}{H} = a + b \left(\frac{H}{H_o} \right)^{-1} \quad (16)$$

$$H_d = a + b \left(\frac{H}{H_o} \right) \quad (17)$$

Ezekwe and Ezeilo [33] developed the following MB models in Nsukka

For January to May

$$\frac{H_d}{H} = 1.13 - 1.48 \left(\frac{H}{H_o} \right) \quad (18a)$$

For dry season

$$\frac{H_d}{H} = 1.14 - 1.69 \left(\frac{H}{H_o} \right) \quad (18b)$$

Said and Ibrahim [34] developed the following MB model for Cairo, Egypt as:

$$\frac{H_d}{H} = 0.86 - 0.86 \left(\frac{H}{H_o} \right) \quad (19)$$

Maduekwe and Chendo [35] developed HB diffuse solar radiation for Lagos as:

$$\frac{H_d}{H} = 1.021 - 0.151 \left(\frac{H}{H_o} \right) \quad 0 \leq \left(\frac{H}{H_o} \right) \leq 0.30 \quad (20a)$$

$$\frac{H_d}{H} = 1.385 - 1.396 \left(\frac{H}{H_o} \right) \quad 0.30 < \left(\frac{H}{H_o} \right) < 0.80 \quad (20b)$$

Babatunde and Aro [36] established the following MB model for Ilorin as:

$$\frac{H_d}{H} = 0.945 - 0.97 \left(\frac{H}{H_o} \right) \quad (21)$$

Maduekwe and Chendo [37] proposed the following HB models for Lagos

$$\frac{H_d}{H} = 1.021 - 1.151 \left(\frac{H}{H_o} \right) \quad 0 \leq \left(\frac{H}{H_o} \right) \leq 0.30 \quad (22a)$$

$$\frac{H_d}{H} = 1.385 - 1.396 \left(\frac{H}{H_o} \right) \quad 0.30 < \left(\frac{H}{H_o} \right) < 0.80 \quad (22b)$$

Trabea [38] obtained the following MB model for AL-Arish, AL-Tahrir, Marsa Matroh, Cairo, Al-Kharga and Aswan located in Egypt as:

$$\frac{H_d}{H} = 0.924 - 0.894 \left(\frac{H}{H_o} \right) \quad (23)$$

Maduekwe and Garba [39] developed the following HB models for Lagos and Zaria with the appropriate intervals as:

For Zaria

$$\frac{H_d}{H} = 1.009 - 0.273 \left(\frac{H}{H_o} \right) \quad \left(\frac{H}{H_o} \right) \leq 0.18 \quad (24a)$$

$$\frac{H_d}{H} = 1.077 - 1.136 \left(\frac{H}{H_o} \right) \quad 0.18 < \left(\frac{H}{H_o} \right) < 0.68 \quad (24b)$$

For Lagos

$$\frac{H_d}{H} = 1.002 - 0.028 \left(\frac{H}{H_o} \right) \quad \left(\frac{H}{H_o} \right) \leq 0.20 \quad (24c)$$

$$\frac{H_d}{H} = 1.336 - 1.369 \left(\frac{H}{H_o} \right) \quad 0.20 < \left(\frac{H}{H_o} \right) < 0.78 \quad (24d)$$

Shaltout *et al.* [40] developed the following MB models for Cario and Aswan in Egypt.

For Cario

$$\frac{H_d}{H} = 0.93 - 1.08 \left(\frac{H}{H_o} \right) \quad (25a)$$

For Aswan

$$\frac{H_d}{H} = 1.01 - 1.16 \left(\frac{H}{H_o} \right) \quad (25b)$$

El-Sebail and Trabea [41] developed the following MB models for four Egyptian locations'

For Matruh

$$\frac{H_d}{H} = 1.299 - 1.435 \left(\frac{H}{H_o} \right) \quad (26a)$$

For Al-Arish

$$\frac{H_d}{H} = 1.377 - 1.550 \left(\frac{H}{H_o} \right) \quad (26b)$$

For Rafah

$$\frac{H_d}{H} = 1.257 - 1.531 \left(\frac{H}{H_o} \right) \quad (26c)$$

For Aswan

$$\frac{H_d}{H} = 0.580 - 0.339 \left(\frac{H}{H_o} \right) \quad (26d)$$

Burari [42] developed the following MB models for Bauchi as follows:

$$\frac{H_d}{H} = 0.775 - 0.804 \left(\frac{H}{H_o} \right) \quad (27)$$

Ugwuoke and Okeke [43] developed the following models for Nsukka as:

$$H_d = 0.137255 - 0.1143 \left(\frac{H}{H_o} \right) \quad (28)$$

Khalil and Shaffie [44] established the following HB models for Cario, Egypt as:

$$\frac{H_d}{H} = 5.817 - 6.517 \left(\frac{H}{H_o} \right) \quad (29)$$

Okundamiya *et al.* [45] established the following MB models for six Nigerian locations

For Sokoto

$$\frac{H_d}{H} = 1.0658 - 1.2566 \left(\frac{H}{H_o} \right) \quad (30a)$$

For Maiduguri

$$\frac{H_d}{H} = 1.0600 - 1.2526 \left(\frac{H}{H_o} \right) \quad (30b)$$

For Abuja

$$\frac{H_d}{H} = 1.0506 - 1.2461 \left(\frac{H}{H_o} \right) \quad (30c)$$

For Ikeja

$$\frac{H_d}{H} = 1.0467 - 1.2461 \left(\frac{H}{H_o} \right) \quad (30d)$$

For Enugu

$$\frac{H_d}{H} = 1.0454 - 1.2467 \left(\frac{H}{H_o} \right) \quad (30e)$$

For Benin City

$$\frac{H_d}{H} = 1.0387 - 1.2419 \left(\frac{H}{H_o} \right) \quad (30f)$$

Nwokolo and Ogbulezie [10] developed the following MB models for all sky and clear sky in numerous stations in six tropical ecological zones in Nigeria.

For Port Harcourt (All sky)

$$H_d = 14.273 - 13.50 \left(\frac{H}{H_o} \right) \quad (31a)$$

For Port Harcourt (Clear sky)

$$H_d = -1.874 + 16.922 \left(\frac{H}{H_o} \right) \quad (31b)$$

For Owerri (All sky)

$$H_d = 10.814 - 7.031 \left(\frac{H}{H_o} \right) \quad (31c)$$

For Owerri (Clear Sky)

$$H_d = -5.400 + 23.21 \left(\frac{H}{H_o} \right) \quad (31d)$$

For Ibadan (All sky)

$$H_d = 12.059 - 9.542 \left(\frac{H}{H_o} \right) \quad (31e)$$

For Ibadan (Clear Sky)

$$H_d = -7.4955 + 26.902 \left(\frac{H}{H_o} \right) \quad (31f)$$

For Abuja (All sky)

$$H_d = 14.076 - 13.008 \left(\frac{H}{H_o} \right) \quad (31g)$$

For Abuja (clear sky)

$$H_d = 35.705 - 49.757 \left(\frac{H}{H_o} \right) \quad (31h)$$

For Maiduguri (All sky)

$$H_d = 18.049 - 19.256 \left(\frac{H}{H_o} \right) \quad (31i)$$

For Maiduguri (clear sky)

$$H_d = 33.121 - 45.136 \left(\frac{H}{H_o} \right) \quad (31j)$$

For Sokoto (All sky)

$$H_d = 19.008 - 20.404 \left(\frac{H}{H_o} \right) \quad (31k)$$

For Sokoto (Clear sky)

$$H_d = 7.8579 - 3.1059 \left(\frac{H}{H_o} \right) \quad (31L)$$

4.1.2. Group 2

Empirical models from this group are parameterized as the second-order polynomial function of the clearness index according to their functional forms and developing year. The functional forms are as follows:

$$\frac{H_d}{H} = a + b \left(\frac{H}{H_o} \right) + c \left(\frac{H}{H_o} \right)^2 \quad (32)$$

Trabea [38] obtained the following MB model for AL-Arish, AL-Tahrir, Marsa Matroh, Cairo, Al-Kharga and Aswan located in Egypt as:

$$\frac{H_d}{H} = 0.534 + 0.384 \left(\frac{H}{H_o} \right) - 1.0366 \left(\frac{H}{H_o} \right)^2 \quad (33)$$

El-Sebaai and Trabea [41] developed the following MB models for four Egyptian locations' For Matruh

$$\frac{H_d}{H} = -4.914 + 18.170 \left(\frac{H}{H_o} \right) - 15.439 \left(\frac{H}{H_o} \right)^2 \quad (34a)$$

For Al-Arish

$$\frac{H_d}{H} = -4.138 + 16.540 \left(\frac{H}{H_o} \right) - 14.778 \left(\frac{H}{H_o} \right)^2 \quad (34b)$$

For Rafah

$$\frac{H_d}{H} = 2.635 - 5.652 \left(\frac{H}{H_o} \right) + 3.312 \left(\frac{H}{H_o} \right)^2 \quad (34c)$$

For Aswan

$$\frac{H_d}{H} = 10.45 - 29.47 \left(\frac{H}{H_o} \right) + 21.459 \left(\frac{H}{H_o} \right)^2 \quad (34d)$$

Burari [42] developed the following MB models for Bauchi as follows:

$$\frac{H_d}{H} = 0.908 - 1.31 \left(\frac{H}{H_o} \right) + 0.474 \left(\frac{H}{H_o} \right)^2 \quad (35)$$

Okundamiya and Nzeako [46] developed the following MB models for selected cities in Nigeria

For Abuja

$$\frac{H_d}{H} = 0.8733 - 0.5902 \left(\frac{H}{H_o} \right) - 0.583 \left(\frac{H}{H_o} \right)^2 \quad (36a)$$

For Benin City

$$\frac{H_d}{H} = 0.9467 - 0.809 \left(\frac{H}{H_o} \right) - 0.4755 \left(\frac{H}{H_o} \right)^2 \quad (36b)$$

For Katisna

$$\frac{H_d}{H} = 3.031 - 7.64 \left(\frac{H}{H_o} \right) - 5.166 \left(\frac{H}{H_o} \right)^2 \quad (36c)$$

Sanusi and Abisoye [47] proposed the following MB models for Lagos, Nigeria as:

$$\frac{H_d}{H} = 0.9676 - 1.2654 \left(\frac{H}{H_o} \right) + 0.3199 \left(\frac{H}{H_o} \right)^2 \quad (37)$$

Okundamiya *et al.* [45] established the following MB models for six Nigerian locations

For Sokoto

$$\frac{H_d}{H} = 1.1198 - 1.4433 \left(\frac{H}{H_o} \right) + 0.1600 \left(\frac{H}{H_o} \right)^2 \quad (38a)$$

For Maiduguri

$$\frac{H_d}{H} = 0.7087 - 0.0103 \left(\frac{H}{H_o} \right) - 1.0845 \left(\frac{H}{H_o} \right)^2 \quad (38b)$$

For Abuja

$$\frac{H_d}{H} = 0.8994 - 0.6674 \left(\frac{H}{H_o} \right) - 0.5466 \left(\frac{H}{H_o} \right)^2 \quad (38c)$$

For Ikeja

$$\frac{H_d}{H} = 0.9225 - 0.7240 \left(\frac{H}{H_o} \right) - 0.5340 \left(\frac{H}{H_o} \right)^2 \quad (38d)$$

For Enugu

$$\frac{H_d}{H} = 0.9571 - 0.8786 \left(\frac{H}{H_o} \right) - 0.3753 \left(\frac{H}{H_o} \right)^2 \quad (38e)$$

For Benin City

$$\frac{H_d}{H} = 0.9994 - 1.0627 \left(\frac{H}{H_o} \right) - 0.1983 \left(\frac{H}{H_o} \right)^2 \quad (38f)$$

Nwokolo and Ogbulezie [10] developed the following MB models for all sky and clear sky in several locations in six tropical ecological zones in Nigeria.

For Port Harcourt (All Sky)

$$\frac{H_d}{H} = 1.011 - 1.091 \left(\frac{H}{H_o} \right) - 0.195 \left(\frac{H}{H_o} \right)^2 \quad (39a)$$

For Port Harcourt (Clear Sky)

$$\frac{H_d}{H} = -34.62 + 122.42\left(\frac{H}{H_o}\right) - 106.44\left(\frac{H}{H_o}\right)^2 \quad (39b)$$

For Owerri (All Sky)

$$\frac{H_d}{H} = 0.987 - 1.003\left(\frac{H}{H_o}\right) - 0.257\left(\frac{H}{H_o}\right)^2 \quad (39c)$$

For Owerri (Clear Sky)

$$\frac{H_d}{H} = -13.81 + 47.749\left(\frac{H}{H_o}\right) - 39.80\left(\frac{H}{H_o}\right)^2 \quad (39d)$$

For Ibadan (All Sky)

$$\frac{H_d}{H} = 0.942 - 0.825\left(\frac{H}{H_o}\right) - 0.447\left(\frac{H}{H_o}\right)^2 \quad (39e)$$

For Ibadan (Clear Sky)

$$\frac{H_d}{H} = 20.86 - 77.77\left(\frac{H}{H_o}\right) - 73.75\left(\frac{H}{H_o}\right)^2 \quad (39f)$$

For Abuja (All Sky)

$$\frac{H_d}{H} = 0.981 - 1.020\left(\frac{H}{H_o}\right) - 0.195\left(\frac{H}{H_o}\right)^2 \quad (39g)$$

For Abuja (Clear Sky)

$$\frac{H_d}{H} = -49.95 + 175.55\left(\frac{H}{H_o}\right) - 153.0\left(\frac{H}{H_o}\right)^2 \quad (39h)$$

For Maiduguri (All Sky)

$$\frac{H_d}{H} = 0.907 - 0.721\left(\frac{H}{H_o}\right) - 0.456\left(\frac{H}{H_o}\right)^2 \quad (39i)$$

For Maiduguri (Clear Sky)

$$\frac{H_d}{H} = 29.75 - 96.05\left(\frac{H}{H_o}\right) + 78.178\left(\frac{H}{H_o}\right)^2 \quad (39j)$$

For Sokoto (All Sky)

$$\frac{H_d}{H} = 2.132 - 4.750\left(\frac{H}{H_o}\right) - 2.852\left(\frac{H}{H_o}\right)^2 \quad (39k)$$

For Sokoto (Clear Sky)

$$\frac{H_d}{H} = 0.678 - 1.082\left(\frac{H}{H_o}\right) + 0.001\left(\frac{H}{H_o}\right)^2 \quad (39L)$$

4.1.3. Group 3

Empirical models from this group are parameterized as the third-order polynomial function of the clearness index according to their functional forms and developing year. The functional forms are as follows:

$$\frac{H_d}{H} = a + b\left(\frac{H}{H_o}\right) + c\left(\frac{H}{H_o}\right)^2 + d\left(\frac{H}{H_o}\right)^3 \quad (40)$$

Said and Ibrahim [34] developed the following MB model for Cairo, Egypt as:

$$\frac{H_d}{H} = 0.636 - 0.279\left(\frac{H}{H_o}\right) - 0.194\left(\frac{H}{H_o}\right)^2 - 0.383\left(\frac{H}{H_o}\right)^3 \quad (41)$$

El-Sebaei and Trabea [41] developed the following MB models for four Egyptian locations' For Matruh

$$\frac{H_d}{H} = 113.3 - 540.92\left(\frac{H}{H_o}\right) - 564.79\left(\frac{H}{H_o}\right)^2 + 461.38\left(\frac{H}{H_o}\right)^3 \quad (42a)$$

For Rafah

$$\frac{H_d}{H} = 6.140 - 22.58\left(\frac{H}{H_o}\right) + 30.519\left(\frac{H}{H_o}\right)^2 - 14.543\left(\frac{H}{H_o}\right)^3 \quad (42b)$$

For Aswan

$$\frac{H_d}{H} = -65.81 - 306.75\left(\frac{H}{H_o}\right) - 472.70\left(\frac{H}{H_o}\right)^2 + 241.42\left(\frac{H}{H_o}\right)^3 \quad (42c)$$

Olopade and Sanusi [48] developed the following MB model for Ilorin as:

$$\frac{H_d}{H} = 0.910 + 1.154\left(\frac{H}{H_o}\right) - 4.936\left(\frac{H}{H_o}\right)^2 + 2.848\left(\frac{H}{H_o}\right)^3 \quad 0.1 \leq \left(\frac{H}{H_o}\right) \leq 0.7 \quad (43)$$

Okundamiya *et al.* [45] established the following MB models for six Nigerian locations For Sokoto

$$\frac{H_d}{H} = 2.1699 - 6.9082\left(\frac{H}{H_o}\right) + 9.592\left(\frac{H}{H_o}\right)^2 - 5.4009\left(\frac{H}{H_o}\right)^3 \quad (44a)$$

For Maiduguri

$$\frac{H_d}{H} = 7.3138 - 35.4344\left(\frac{H}{H_o}\right) + 61.7977\left(\frac{H}{H_o}\right)^2 - 36.9520\left(\frac{H}{H_o}\right)^3 \quad (44b)$$

For Abuja

$$\frac{H_d}{H} = 2.7317 - 11.346\left(\frac{H}{H_o}\right) + 19.9398\left(\frac{H}{H_o}\right)^2 - 12.9301\left(\frac{H}{H_o}\right)^3 \quad (44c)$$

For Ikeja

$$\frac{H_d}{H} = 2.3663 - 9.8575\left(\frac{H}{H_o}\right) + 18.4150\left(\frac{H}{H_o}\right)^2 - 12.90721\left(\frac{H}{H_o}\right)^3 \quad (44d)$$

For Enugu

$$\frac{H_d}{H} = 2.5887 - 11.1174 \left(\frac{H}{H_o} \right) + 20.7699 \left(\frac{H}{H_o} \right)^2 - 14.3774 \left(\frac{H}{H_o} \right)^3 \quad (44e)$$

For Benin City

$$\frac{H_d}{H} = 2.3880 - 10.5426 \left(\frac{H}{H_o} \right) + 21.0098 \left(\frac{H}{H_o} \right)^2 - 15.5605 \left(\frac{H}{H_o} \right)^3 \quad (44f)$$

4.1.4. Group 4

Empirical models from this group are parameterized as the four-order polynomial function of the clearness index according to their functional forms and developing year. The functional forms are as follows:

$$\frac{H_d}{H} = a + b \left(\frac{H}{H_o} \right) + c \left(\frac{H}{H_o} \right)^2 + d \left(\frac{H}{H_o} \right)^3 + e \left(\frac{H}{H_o} \right)^4 \quad (45)$$

Bamiro [49] developed the following HB models for Nsukka as:

$$\frac{H_d}{H} = 1.0 - 0.2727 \left(\frac{H}{H_o} \right) + 2.4495 \left(\frac{H}{H_o} \right)^2 - 11.9514 \left(\frac{H}{H_o} \right)^3 + 9.3879 \left(\frac{H}{H_o} \right)^4 \left(\frac{H}{H_o} \right) < 0.715 \quad (46a)$$

(46a)

$$\frac{H_d}{H} = 1.0 + 0.2832 \left(\frac{H}{H_o} \right) - 2.555 \left(\frac{H}{H_o} \right)^2 + 0.8448 \left(\frac{H}{H_o} \right)^3 + 9.3879 \left(\frac{H}{H_o} \right)^4 \left(\frac{H}{H_o} \right) < 0.722 \quad (46b)$$

(46b)

4.1.5 Group 5

In this sub-class, exponential form of diffuse fraction was correlated with clearness index in forms:

$$\frac{H_d}{H} = a \exp^{b \left(\frac{H}{H_o} \right)} \quad (47)$$

Sanusi and Abisoye [47] proposed the following MB models for Lagos, Nigeria as:

$$\frac{H_d}{H} = 1.2313 \exp^{-2.2 \left(\frac{H}{H_o} \right)} \quad (48)$$

4.1.6 Group 6

In this sub-class, Liu and Jordan type model was modified by correlating diffuse fraction with power form of clearness index in the form:

$$\frac{H_d}{H} = a \left(\frac{H}{H_o} \right)^b \quad (49)$$

Sanusi and Abisoye [47] proposed the following MB models for Lagos, Nigeria as:

$$\frac{H_d}{H} = 0.2 \left(\frac{H}{H_o} \right)^{-1.012} \quad (50)$$

4.2 Sunshine-Based Models

Sunshine-based models are the most frequently employed model for predicting diffuse solar radiation in Nigeria and Egypt as a result of its availability and reliable measured data in most meteorological stations in Nigeria and Egypt. This radiometric model modified from Liu and Jordan [11] model have been applied by countless number of researchers for predicting the hourly, daily and monthly mean daily diffuse solar radiation on the horizontal surface for several stations within Nigeria and Egypt and beyond by employing meteorological parameters of the site of interest as stated in this class. Thus, the relation is given as:

$$\frac{H}{H_o} = a + b \left(\frac{S}{S_o} \right) \quad (51)$$

Where a and b are the empirical constants, S is the measure of sunshine duration and S_o is the daily maximum possible sunshine duration.

4.2.1 Group 1

Empirical models from this group are parameterized as the first-order polynomial function of the sunshine fraction according to their functional forms and developing year. The functional forms are as follows:

$$\frac{H_d}{H} = a + b \left(\frac{S}{S_o} \right) \quad (52)$$

$$\frac{H_d}{H_o} = a + b \left(\frac{S}{S_o} \right) \quad (53)$$

Said and Ibrahim [34] developed the following MB model for Cairo, Egypt as:

$$\frac{H_d}{H} = 0.79 - 0.59 \left(\frac{S}{S_o} \right) \quad (54)$$

Maduekwe and Chendo [37] developed the following DB and MB models for Lagos.

For DB

$$\frac{H_d}{H_o} = -0.012 + 0.46 \left(\frac{S}{S_o} \right) \quad (55a)$$

$$\frac{H_d}{H} = 0.078 + 0.58 \left(\frac{S}{S_o} \right) \quad (55b)$$

For MB

$$\frac{H_d}{H} = 0.82 - 0.39 \left(\frac{S}{S_o} \right) \quad (55c)$$

Trabea [38] obtained the following MB model for AL-Arish, AL-Tahrir, Marsa Matroh, Cairo, Al-Kharga and Aswan located in Egypt as:

$$\frac{H_d}{H} = 0.896 - 0.688 \left(\frac{S}{S_o} \right) \quad (56)$$

El-Sebail and Trabea [41] developed the following MB models for four Egyptian locations' For Matruh

$$\frac{H_d}{H} = 0.618 - 0.335 \left(\frac{S}{S_o} \right) \quad (57a)$$

$$\frac{H_d}{H_o} = 0.352 - 0.154 \left(\frac{S}{S_o} \right) \quad (57b)$$

For Al-Arish

$$\frac{H_d}{H} = 0.941 - 0.683 \left(\frac{S}{S_o} \right) \quad (57c)$$

$$\frac{H_d}{H_o} = 0.463 - 0.271 \left(\frac{S}{S_o} \right) \quad (57d)$$

For Rafah

$$\frac{H_d}{H} = 0.730 - 0.433 \left(\frac{S}{S_o} \right) \quad (57e)$$

$$\frac{H_d}{H_o} = 0.378 - 0.171 \left(\frac{S}{S_o} \right) \quad (57f)$$

For Aswan

$$\frac{H_d}{H} = 0.886 - 0.618 \left(\frac{S}{S_o} \right) \quad (57g)$$

$$\frac{H_d}{H_o} = 0.627 - 0.453 \left(\frac{S}{S_o} \right) \quad (57h)$$

Khalil and Shaffie [44] established the following HB models for Cairo, Egypt as:

$$\frac{H_d}{H} = 8.342 - 6.455 \left(\frac{S}{S_o} \right) \quad (58a)$$

$$\frac{H_d}{H_o} = 3.815 - 5.319 \left(\frac{S}{S_o} \right) \quad (58b)$$

4.2.2 Group 2

Empirical models from this group are parameterized as the second-order polynomial function of the sunshine fraction according to their functional forms and developing year. The functional forms are as follows:

$$\frac{H_d}{H_o} = a + b \left(\frac{S}{S_o} \right) + c \left(\frac{S}{S_o} \right)^2 \quad (59a)$$

$$\frac{H_d}{H} = a + b \left(\frac{S}{S_o} \right) + c \left(\frac{S}{S_o} \right)^2 \quad (59b)$$

Said and Ibrahim [34] developed the following MB model for Cairo, Egypt as:

$$\frac{H_d}{H_o} = 0.252 - 0.0001 \left(\frac{S}{S_o} \right) - 0.083 \left(\frac{S}{S_o} \right)^2 \quad (60)$$

Maduekwe and Chendo [37] developed the following DB and MB models for Lagos.

For DB

$$\frac{H_d}{H_o} = 0.018 + 0.30 \left(\frac{S}{S_o} \right) + 0.167 \left(\frac{S}{S_o} \right)^2 \quad (61a)$$

$$\frac{H_d}{H} = 0.083 + 0.56 \left(\frac{S}{S_o} \right) + 0.029 \left(\frac{S}{S_o} \right)^2 \quad (61b)$$

For MB

$$\frac{H_d}{H_o} = 0.384 - 0.25 \left(\frac{S}{S_o} \right) + 0.31 \left(\frac{S}{S_o} \right)^2 \quad (61c)$$

$$\frac{H_d}{H} = 0.824 - 0.55 \left(\frac{S}{S_o} \right) + 0.377 \left(\frac{S}{S_o} \right)^2 \quad (61d)$$

Trabea [38] obtained the following MB model for AL-Arish, AL-Tahrir, Marsa Matroh, Cairo, Al-Kharga and Aswan located in Egypt as:

$$\frac{H_d}{H} = 0.839 - 0.537 \left(\frac{S}{S_o} \right) - 0.098 \left(\frac{S}{S_o} \right)^2 \quad (62a)$$

$$\frac{H_d}{H_o} = 0.101 + 1.092 \left(\frac{S}{S_o} \right) - 0.854 \left(\frac{S}{S_o} \right)^2 \quad (62b)$$

$$\frac{H_d}{H_o} = -7.0744 + 31.4386 \left(\frac{S}{S_o} \right) - 15.5906 \left(\frac{S}{S_o} \right)^2 \quad 0.6 \leq \left(\frac{H}{H_o} \right) \leq 0.8 \quad (62c)$$

El-Sebaai and Trabea [41] developed the following MB models for four Egyptian locations' For Matruh

$$\frac{H_d}{H} = 0.113 + 1.198 \left(\frac{S}{S_o} \right) - 1.116 \left(\frac{S}{S_o} \right)^2 \quad (63a)$$

$$\frac{H_d}{H_o} = -0.012 + 0.948 \left(\frac{S}{S_o} \right) - 0.802 \left(\frac{S}{S_o} \right)^2 \quad (63b)$$

For Al-Arish

$$\frac{H_d}{H} = -1.888 + 6.999 \left(\frac{S}{S_o} \right) - 5.144 \left(\frac{S}{S_o} \right)^2 \quad (63c)$$

$$\frac{H_d}{H_o} = -1.353 + 4.659 \left(\frac{S}{S_o} \right) - 3.301 \left(\frac{S}{S_o} \right)^2 \quad (63d)$$

For Rafah

$$\frac{H_d}{H} = -2.053 + 7.440 \left(\frac{S}{S_o} \right) - 5.468 \left(\frac{S}{S_o} \right)^2 \quad (63e)$$

$$\frac{H_d}{H_o} = -1.052 + 3.875\left(\frac{S}{S_o}\right) - 2.810\left(\frac{S}{S_o}\right)^2 \quad (63f)$$

For Aswan

$$\frac{H_d}{H} = 3.431 - 6.602\left(\frac{S}{S_o}\right) + 3.506\left(\frac{S}{S_o}\right)^2 \quad (63g)$$

$$\frac{H_d}{H_o} = 1.665 - 2.892\left(\frac{S}{S_o}\right) + 1.429\left(\frac{S}{S_o}\right)^2 \quad (63h)$$

4.2.3 Group 3

Empirical models from this group are parameterized as the third-order polynomial function of the sunshine fraction according to their functional forms and developing year.

The functional forms are as follows:

$$\frac{H_d}{H} = a + b\left(\frac{S}{S_o}\right) + c\left(\frac{S}{S_o}\right)^2 + d\left(\frac{S}{S_o}\right)^3 \quad (64)$$

$$\frac{H_d}{H_o} = a + b\left(\frac{S}{S_o}\right) + c\left(\frac{S}{S_o}\right)^2 + d\left(\frac{S}{S_o}\right)^3 \quad (65)$$

El-Sebaai and Trabea [41] developed the following MB models for four Egyptian locations'

For Matruh

$$\frac{H_d}{H} = 0.148 - 0.126\left(\frac{S}{S_o}\right) - 0.862\left(\frac{S}{S_o}\right)^2 + 1.031\left(\frac{S}{S_o}\right)^3 \quad (66a)$$

$$\frac{H_d}{H_o} = -0.622 + 3.813\left(\frac{S}{S_o}\right) - 5.165\left(\frac{S}{S_o}\right)^2 + 2.159\left(\frac{S}{S_o}\right)^3 \quad (66b)$$

For Al-Arish

$$\frac{H_d}{H} = -19.58 + 79.25\left(\frac{S}{S_o}\right) - 102.89\left(\frac{S}{S_o}\right)^2 + 43.79\left(\frac{S}{S_o}\right)^3 \quad (66c)$$

$$\frac{H_d}{H_o} = -17.32 + 69.89\left(\frac{S}{S_o}\right) - 91.55\left(\frac{S}{S_o}\right)^2 + 39.53\left(\frac{S}{S_o}\right)^3 \quad (66d)$$

For Rafah

$$\frac{H_d}{H} = 4.129 - 19.02\left(\frac{S}{S_o}\right) + 31.94\left(\frac{S}{S_o}\right)^2 - 17.47\left(\frac{S}{S_o}\right)^3 \quad (66e)$$

$$\frac{H_d}{H_o} = -1.293 + 4.903\left(\frac{S}{S_o}\right) - 4.263\left(\frac{S}{S_o}\right)^2 + 0.679\left(\frac{S}{S_o}\right)^3 \quad (66f)$$

For Aswan

$$\frac{H_d}{H} = -24.32 + 90.86\left(\frac{S}{S_o}\right) - 110.38\left(\frac{S}{S_o}\right)^2 + 44.281\left(\frac{S}{S_o}\right)^3 \quad (66g)$$

$$\frac{H_d}{H_o} = -17.95 + 65.10\left(\frac{S}{S_o}\right) - 79.07\left(\frac{S}{S_o}\right)^2 + 31.299\left(\frac{S}{S_o}\right)^3 \quad (66h)$$

Okundamiya *et al.* [45] established the following MB models for six Nigerian locations

For Sokoto

$$\frac{H_d}{H_o} = 0.6923 - 1.4582\left(\frac{S}{S_o}\right) + 1.2132\left(\frac{S}{S_o}\right)^2 - 0.2869\left(\frac{S}{S_o}\right)^3 \quad (67a)$$

For Maiduguri

$$\frac{H_d}{H_o} = 0.6226 - 1.2632\left(\frac{S}{S_o}\right) + 1.0499\left(\frac{S}{S_o}\right)^2 - 0.2354\left(\frac{S}{S_o}\right)^3 \quad (67b)$$

For Abuja

$$\frac{H_d}{H_o} = 0.1485 - 2.2775\left(\frac{S}{S_o}\right) + 4.3429\left(\frac{S}{S_o}\right)^2 + 2.4702\left(\frac{S}{S_o}\right)^3 \quad (67c)$$

For Ikeja

$$\frac{H_d}{H_o} = -1.2813 + 13.4719\left(\frac{S}{S_o}\right) - 39.3713\left(\frac{S}{S_o}\right)^2 + 37.1341\left(\frac{S}{S_o}\right)^3 \quad (67d)$$

For Enugu

$$\frac{H_d}{H_o} = 0.1179 + 0.7339\left(\frac{S}{S_o}\right) - 1.5841\left(\frac{S}{S_o}\right)^2 + 0.9322\left(\frac{S}{S_o}\right)^3 \quad (67e)$$

For Benin City

$$\frac{H_d}{H_o} = 0.2015 + 0.0459\left(\frac{S}{S_o}\right) + 0.1159\left(\frac{S}{S_o}\right)^2 - 0.4154\left(\frac{S}{S_o}\right)^3 \quad (67f)$$

4.3 Cloud Cover-Based models

Cloud cover as a climate variable is the fraction of the sky obscured by clouds when observed from a given locality. Cloud cover data are periodically obtained from meteorological stations or satellites-derived and are expressed in percent (%) of the maximum cloud amount. Cloud amount is mostly classified into several categories of 0 – 24%, 25 – 49%, 50 – 74% and 75 – 100%. The implication is that zero percent implies no visible cloud in the sky while hundred percent cloud amount indicates no clear sky is visible. Researchers in the domain of renewable energy in the past have investigated and simulated regression computing models to relate cloud amount conditions and diffuse solar radiation owing to the fact that as diffuse fraction or diffuse coefficient increases, clouds cover increases as well. This is because of the absorption of water vapour's waveband selective in the solar spectrum that is, in cloudy and humid conditions, the absorption of solar radiation in the infrared portion of the solar spectrum is enhanced whereas absorption in

the diffuse solar radiation waveband does not vary significantly as shown in the relations below.

4.3.1. Group 1

Empirical models from this group are parameterized as the first-order polynomial function of the diffuse fraction or diffuse coefficient with cloud cover (C) or cloudiness index according to their functional forms and developing year. The functional forms are as follows:

$$\frac{H_d}{H} = a + b(C) \quad (68)$$

$$\frac{H_d}{H} = a + b\left(\frac{C}{8}\right) \quad (69)$$

$$\frac{H_d}{H_o} = a + b\left(\frac{C}{8}\right) \quad (70)$$

Erusiafe and Chendo [50] developed HB model for Lagos as:

$$\frac{H_d}{H} = -0.0859 + 1.316(C) \quad (71)$$

Okundamiya *et al.* [45] established the following MB models for six Nigerian locations
For Sokoto

$$\frac{H_d}{H} = 0.1505 - 0.0439(C) \quad (72a)$$

For Maiduguri

$$\frac{H_d}{H} = 0.1202 - 0.0528(C) \quad (72b)$$

For Abuja

$$\frac{H_d}{H} = 0.1052 - 0.0614(C) \quad (72c)$$

For Ikeja

$$\frac{H_d}{H} = 0.0792 - 0.0706(C) \quad (72d)$$

For Enugu

$$\frac{H_d}{H} = 0.0888 - 0.0669(C) \quad (72e)$$

For Benin City

$$\frac{H_d}{H} = 0.0761 - 0.0759(C) \quad (72f)$$

4.4 Monthly-Based Models

Monthly-based models are applied for estimating diffuse solar radiation as a result of variation effects on diffuse solar radiation striking at ground level in a particular location due to the movement on the earth on its axis. Thus, the functional forms and models employed in Africa are introduced in this section.

4.4.1 Group 1

In this group, clearness index is corrected to month of the year (M) in the form:

$$H_d = a + b(M) + c(M)^2 + d(M)^3 \quad (73)$$

Ugwuoke and Okeke [43] developed the following models for Nsukka as:

$$H_d = 47.2667 - 6.5095(M) + 0.8832(M)^2 - 0.03918(M)^3 \quad (74)$$

4.5 Global Solar Radiation-Based models

Global solar radiation-based models are employed by solar radiation researchers for predicting diffuse solar radiation as a result of their great importance and influence for determining the diffuse solar radiation striking a particular location at the top of the atmosphere and their comprehensive impact on the diffuse solar radiation on the horizontal surface on ground level. Thus, the functional forms and models employed in Africa are presented in this section.

4.5.1 Group 1

In this group, diffuse solar radiation is correlated to global solar radiation (H) in the form:

$$H_d = a + b(H) + c(H)^2 \quad (75)$$

Ugwuoke and Okeke [43] developed the following models for Nsukka as:

$$H_d = 62.53439 - 12.75992(H) + 0.9774(H)^2 \quad (76)$$

4.6 Hybrid Parameter-based models

As far as the input parameter for predicting diffuse solar radiation on the horizontal surface vary periodically with the local climate in a particular geographical location, it therefore implies that to accurately develop a model that can fit a locality, the solar energy researcher must test the local climate with various input parameters owing to the availability of the meteorological parameters at the disposal of the researcher. Several solar energy researchers in Nigeria and Egypt have observed that hybrid parameters-based models fit local climate more than one variable – sunshine-based, global solar radiation-based and cloud cover – based commonly employed for predicting diffuse solar radiation. In this section, numerous hybrid parameter-based models are presented and classified based on their input parameters and developing year.

4.6.1 Group 1

In this group, sunshine duration and clearness index were incorporated with diffuse for estimating diffuse solar radiation in the forms:

$$\frac{H_d}{H_o} = a + b\left(\frac{H}{H_o}\right) + c\left(\frac{S}{S_o}\right) \quad (77)$$

$$\frac{H_d}{H_o} = a + b\left(\frac{H}{H_o}\right) + c\left(\frac{S}{S_o}\right) + d\left(\frac{S}{S_o}\right)^2 \quad (78)$$

$$\frac{H_d}{H_o} = a + b\left(\frac{H}{H_o}\right) + c\left(\frac{S}{S_o}\right)^2 \quad (79)$$

$$\frac{H_d}{H} = a + b\left(\frac{H}{H_o}\right) + c\left(\frac{S}{S_o}\right) \quad (80)$$

$$\frac{H_d}{H} = a + b\left(\frac{H}{H_o}\right) + c\left(\frac{S}{S_o}\right) + d\left(\frac{S}{S_o}\right)^2 \quad (81)$$

$$\frac{H_d}{H} = a + b\left(\frac{H}{H_o}\right) + c\left(\frac{S}{S_o}\right)^2 \quad (82)$$

Maduekwe and Chendo [37] developed the following DB and MB models for Lagos.

For DB

$$\frac{H_d}{H_o} = -0.241 - 0.72\left(\frac{H}{H_o}\right) - 0.16\left(\frac{S}{S_o}\right) \quad (83a)$$

$$\frac{H_d}{H_o} = -0.195 - 0.74\left(\frac{H}{H_o}\right) - 0.15\left(\frac{S}{S_o}\right) + 0.324\left(\frac{S}{S_o}\right)^2 \quad (83b)$$

$$\frac{H_d}{H_o} = -0.213 + 0.71\left(\frac{H}{H_o}\right) + 0.182\left(\frac{S}{S_o}\right)^2 \quad (83c)$$

$$\frac{H_d}{H} = -0.17 + 0.78\left(\frac{H}{H_o}\right) + 0.26\left(\frac{S}{S_o}\right) \quad (83d)$$

$$\frac{H_d}{H} = 0.136 + 0.80\left(\frac{H}{H_o}\right) + 0.03\left(\frac{S}{S_o}\right) + 0.235\left(\frac{S}{S_o}\right)^2 \quad (83e)$$

$$\frac{H_d}{H} = -0.133 + 0.81\left(\frac{H}{H_o}\right) + 0.214\left(\frac{S}{S_o}\right)^2 \quad (83f)$$

For MB

$$\frac{H_d}{H_o} = 0.372 - 0.11\left(\frac{H}{H_o}\right) + 0.06\left(\frac{S}{S_o}\right) \quad (83g)$$

$$\frac{H_d}{H_o} = 0.431 - 0.11\left(\frac{H}{H_o}\right) - 0.22\left(\frac{S}{S_o}\right) + 0.300\left(\frac{S}{S_o}\right)^2 \quad (83h)$$

$$\frac{H_d}{H_o} = 0.385 - 0.12\left(\frac{H}{H_o}\right) + 0.067\left(\frac{S}{S_o}\right)^2 \quad (83i)$$

$$\frac{H_d}{H} = 1.36 - 1.35\left(\frac{H}{H_o}\right) - 0.0012\left(\frac{S}{S_o}\right) \quad (83j)$$

$$\frac{H_d}{H} = 1.429 - 1.44\left(\frac{H}{H_o}\right) - 0.17\left(\frac{S}{S_o}\right) + 0.25\left(\frac{S}{S_o}\right)^2 \quad (83k)$$

$$\frac{H_d}{H} = 1.383 - 1.44\left(\frac{H}{H_o}\right) + 0.076\left(\frac{S}{S_o}\right)^2 \quad (83L)$$

Trabea [38] obtained the following MB model for AL-Arish, AL-Tahrir, Marsa Matroh, Cairo, Al-Kharga and Aswan located in Egypt as:

$$\frac{H_d}{H} = 0.9270 - 0.1640 \left(\frac{H}{H_o} \right) - 0.5950 \left(\frac{S}{S_o} \right) \quad (84)$$

Khalil and Shaffie [44] established the following HB models for Cairo, Egypt as:

$$\frac{H_d}{H} = 6.314 - 5.131 \left(\frac{H}{H_o} \right) + 0.136 \left(\frac{S}{S_o} \right) \quad (85a)$$

$$\frac{H_d}{H_o} = 5.292 - 4.226 \left(\frac{H}{H_o} \right) - 0.321 \left(\frac{S}{S_o} \right) \quad (85b)$$

4.6.2 Group 2

In this group, cloud cover and clearness index were incorporated with diffuse for estimating diffuse solar radiation in the forms:

$$\frac{H_d}{H} = a + b \left(\frac{H}{H_o} \right) + c \left(\frac{C}{8} \right) \quad (86)$$

$$\frac{H_d}{H} = a + b \left(\frac{H}{H_o} \right) + c(C) \quad (87)$$

Okundamiya *et al.* [45] established the following MB models for six Nigerian locations
For Sokoto

$$\frac{H_d}{H} = -0.9347 + 0.0154 \left(\frac{H}{H_o} \right) + 0.0154(C) \quad (88a)$$

For Maiduguri

$$\frac{H_d}{H} = 0.8189 - 0.940 \left(\frac{H}{H_o} \right) + 0.0149(C) \quad (88b)$$

For Abuja

$$\frac{H_d}{H} = 0.8760 - 1.0222 \left(\frac{H}{H_o} \right) + 0.0121(C) \quad (88c)$$

For Ikeja

$$\frac{H_d}{H} = 0.8700 - 1.0309 \left(\frac{H}{H_o} \right) + 0.0142(C) \quad (88d)$$

For Enugu

$$\frac{H_d}{H} = 0.8490 - 0.9989 \left(\frac{H}{H_o} \right) + 0.0445(C) \quad (88e)$$

For Benin City

$$\frac{H_d}{H} = 0.8285 - 0.9784 \left(\frac{H}{H_o} \right) + 0.0172(C) \quad (88f)$$

4.6.3 Group 3

In this group, elevation and clearness index were incorporated with diffuse for estimating diffuse solar radiation in the forms:

$$\frac{H_d}{H} = a + b \left(\frac{H}{H_o} \right) + c(h) \quad (89)$$

$$\frac{H_d}{H} = a + b\left(\frac{H}{H_o}\right) + c(\sinh) \quad (90)$$

Maduekwe and Chendo [37] proposed the following HB models for Lagos

$$\frac{H_d}{H} = 1.019 - 0.159\left(\frac{H}{H_o}\right) + 0.0058(\sinh) \quad 0 \leq \left(\frac{H}{H_o}\right) \leq 0.30 \quad (91a)$$

$$\frac{H_d}{H} = 1.550 - 1.469\left(\frac{H}{H_o}\right) + 0.1566(\sinh) \quad 0.30 < \left(\frac{H}{H_o}\right) < 0.80 \quad (91b)$$

$$\frac{H_d}{H} = 0.245\left(\frac{H}{H_o}\right) + 0.085(\sinh) \quad (91c)$$

Maduekwe and Garba [39] developed the following HB models for Lagos and Zaria with the appropriate intervals as:

For Zaria

$$\frac{H_d}{H} = 1.016 - 1.203\left(\frac{H}{H_o}\right) - 0.00455(h) \quad \left(\frac{H}{H_o}\right) \leq 0.18 \quad (92a)$$

$$\frac{H_d}{H} = 0.973 - 0.546\left(\frac{H}{H_o}\right) - 0.00283(h) \quad 0.18 < \left(\frac{H}{H_o}\right) < 0.68 \quad (92b)$$

$$\frac{H_d}{H} = 0.438\left(\frac{H}{H_o}\right) - 0.00104(h) \quad \left(\frac{H}{H_o}\right) \geq 0.68 \quad (92c)$$

For Lagos

$$\frac{H_d}{H} = 1.007 - 0.072\left(\frac{H}{H_o}\right) - 0.000085(h) \quad \left(\frac{H}{H_o}\right) \leq 0.20 \quad (92d)$$

$$\frac{H_d}{H} = 1.36 - 1.246\left(\frac{H}{H_o}\right) - 0.00107(h) \quad 0.20 < \left(\frac{H}{H_o}\right) < 0.78 \quad (92e)$$

$$\frac{H_d}{H} = 0.34\left(\frac{H}{H_o}\right) - 0.00206(h) \quad \left(\frac{H}{H_o}\right) \geq 0.78 \quad (92f)$$

4.6.4 Group 4

In this group, elevation, atmospheric turbidity and clearness index were incorporated with diffuse for estimating diffuse solar radiation in the forms:

$$\frac{H_d}{H} = a + b\left(\frac{H}{H_o}\right) + c(\sinh) + d(\beta) \quad (93)$$

Maduekwe and Chendo [37] proposed the following HB models for Lagos

$$\frac{H_d}{H} = 1.018 - 0.155\left(\frac{H}{H_o}\right) + 0.0037(\sinh) + 0.0032(\beta) \quad 0 \leq \left(\frac{H}{H_o}\right) \leq 0.30 \quad (94a)$$

$$\frac{H_d}{H} = 1.526 - 1.448\left(\frac{H}{H_o}\right) - 0.1679(\sinh) + 0.06704(\beta) \quad 0.30 < \left(\frac{H}{H_o}\right) < 0.80 \quad (94b)$$

$$\frac{H_d}{H} = 0.232\left(\frac{H}{H_o}\right) + 0.0258(\sinh) + 0.24831(\beta) \quad 0.80 \leq \left(\frac{H}{H_o}\right) \quad (94c)$$

4.6.5 Group 5

In this group, solar elevation and clearness index were incorporated with diffuse for estimating diffuse solar radiation in the form:

$$\frac{H_d}{H} = a + b \left(\frac{H}{H_o} \right) + c(Se) \quad (95)$$

Maduekwe and Chendo [35] developed HB diffuse solar radiation for Lagos as:

$$\frac{H_d}{H} = 1.019 - 0.159 \left(\frac{H}{H_o} \right) + 0.0058(Se) \quad 0 \leq \left(\frac{H}{H_o} \right) \leq 0.30 \quad (96a)$$

$$\frac{H_d}{H} = 1.550 - 1.469 \left(\frac{H}{H_o} \right) + 0.1566(Se) \quad 0.30 < \left(\frac{H}{H_o} \right) < 0.80 \quad (96b)$$

$$\frac{H_d}{H} = 0.245 \left(\frac{H}{H_o} \right) + 0.085(Se) \quad 0.80 \leq \left(\frac{H}{H_o} \right) \quad (96c)$$

4.6.6 Group 6

In this group, solar elevation, turbidity coefficients and clearness index were incorporated with diffuse for estimating diffuse solar radiation in the forms:

$$\frac{H_d}{H} = a + b \left(\frac{H}{H_o} \right) + c(Se) + d(\beta_{500}) \quad (97)$$

$$\frac{H_d}{H} = a + b \left(\frac{H}{H_o} \right) + c(Se) + d(\beta_{880}) \quad (98)$$

Maduekwe and Chendo [35] developed HB diffuse solar radiation for Lagos as:

$$\frac{H_d}{H} = 1.018 - 0.155 \left(\frac{H}{H_o} \right) + 0.0037(Se) + 0.00131(\beta_{500}) \quad 0 \leq \left(\frac{H}{H_o} \right) \leq 0.30 \quad (99a)$$

$$\frac{H_d}{H} = 1.526 - 1.448 \left(\frac{H}{H_o} \right) + 0.1679(Se) + 0.02722(\beta_{500}) \quad 0.30 < \left(\frac{H}{H_o} \right) < 0.80 \quad (99b)$$

$$\frac{H_d}{H} = 0.232 \left(\frac{H}{H_o} \right) + 0.0258(Se) + 0.10165(\beta_{500}) \quad 0.80 \leq \left(\frac{H}{H_o} \right) \quad (99c)$$

$$\frac{H_d}{H} = 1.018 - 0.157 \left(\frac{H}{H_o} \right) + 0.0049(Se) + 0.00077(\beta_{880}) \quad 0 \leq \left(\frac{H}{H_o} \right) \leq 0.30 \quad (99d)$$

$$\frac{H_d}{H} = 1.529 - 1.449 \left(\frac{H}{H_o} \right) + 0.1645(Se) + 0.2881(\beta_{880}) \quad 0.30 < \left(\frac{H}{H_o} \right) < 0.80 \quad (99e)$$

$$\frac{H_d}{H} = 0.229 \left(\frac{H}{H_o} \right) + 0.0569(Se) + 0.0838(\beta_{880}) \quad 0.80 \leq \left(\frac{H}{H_o} \right) \quad (99f)$$

4.6.7 Group 7

In this group, sunshine fraction, mean temperature and relative humidity were incorporated with diffuse for estimating diffuse solar radiation in the form:

$$\frac{H_d}{H} = a + b \left(\frac{S}{S_o} \right) + c \left(\frac{S}{S_o} - \theta - R \right) + d \left(\frac{S}{S_o} \right)^2 \quad (100)$$

Sambo and Doyle [51] established the following MB models for Zaria as:

$$\frac{H_d}{H} = 1.325 - 1.960 \left(\frac{S}{S_o} \right) + 0.389 \left(\frac{S}{S_o} - \theta - R \right) + 1.65 \left(\frac{S}{S_o} \right)^2 \quad (101)$$

4.6.8 Group 8

In this group, clearness index, sunshine fraction, mean temperature and relative humidity were incorporated with diffuse for estimating diffuse solar radiation in the form:

$$\frac{H_d}{H} = a + b \left(\frac{H}{H_o} \right) + c \left(\frac{S}{S_o} \right) + d \left(\frac{T_{\max}}{T_{\min}} \right) + e(RH) \quad (102)$$

Falayi *et al.* [52] applied a new combination of meteorological parameters to proposed eight MB models for some nominated locations in Nigeria.

For Sokoto

$$\frac{H_d}{H} = 1.055 - 0.815 \left(\frac{H}{H_o} \right) - 0.0353 \left(\frac{S}{S_o} \right) + 0.142 \left(\frac{T_{\max}}{T_{\min}} \right) + 0.00078(RH) \quad (103a)$$

For Maiduguri

$$\frac{H_d}{H} = 0.7795 - 0.830 \left(\frac{H}{H_o} \right) - 0.0364 \left(\frac{S}{S_o} \right) + 0.152 \left(\frac{T_{\max}}{T_{\min}} \right) + 0.00023(RH) \quad (103b)$$

For Port Harcourt

$$\frac{H_d}{H} = 0.684 - 0.735 \left(\frac{H}{H_o} \right) - 0.095 \left(\frac{S}{S_o} \right) + 0.0248 \left(\frac{T_{\max}}{T_{\min}} \right) + 0.00065(RH) \quad (103c)$$

For Owerri

$$\frac{H_d}{H} = 0.775 - 0.954 \left(\frac{H}{H_o} \right) - 0.056 \left(\frac{S}{S_o} \right) + 0.000042 \left(\frac{T_{\max}}{T_{\min}} \right) + 0.0762(RH) \quad (103d)$$

For Enugu

$$\frac{H_d}{H} = 0.642 - 0.851 \left(\frac{H}{H_o} \right) - 0.044 \left(\frac{S}{S_o} \right) + 0.079 \left(\frac{T_{\max}}{T_{\min}} \right) + 0.0014(RH) \quad (103e)$$

For Yola

$$\frac{H_d}{H} = 1.1007 - 0.9844 \left(\frac{H}{H_o} \right) - 0.0214 \left(\frac{S}{S_o} \right) + 0.1117 \left(\frac{T_{\max}}{T_{\min}} \right) + 0.0001(RH) \quad (103f)$$

For Jos

$$\frac{H_d}{H} = 1.028 - 1.0081 \left(\frac{H}{H_o} \right) - 0.0229 \left(\frac{S}{S_o} \right) + 0.031 \left(\frac{T_{\max}}{T_{\min}} \right) + 0.0011(RH) \quad (103g)$$

5. Discussion

The global sum of regression models reported by peers and researchers for predicting diffuse solar radiation in North-Western Africa is ever increasing and relatively high, which in turn makes it highly laborious to employ statistical indicators such as Root Mean Square Error (RMSE), Sum of the Square of Relative Error (SSRE), Relative Standard Error (RSE), Standard Deviation of the residual (SD), Mean Absolute Bias Error (MABE), Mean Absolute Percentage error (MAPE), coefficient of determination,

uncertainty at 95% (U_{95}), Mean Bias Error (MBE), Mean Percentage Error (MPE), Nash Sutcliffe coefficient (NS), Index of Agreement (IG), Mean Absolute Error (MAE) and Global Performance Indicator (GPI) etc. to select the best approach for a particular site in a single research paper. Recently, Khorasanizadeh and Mohammad [53] classified numerous diffuse solar radiation models across the globe into four categories such as clearness index based-models, sunshine based-model, cloud cover-based models and other meteorological parameter based-models.

Sunshine-based models are frequently applied due to their global availability at most weather stations in North-Western Africa. Cloud cover-based models can be employed in the absence of clearness index and sunshine-based models but are sensible to human biasing [54].

Clearness index based-models are the most frequently applied model for predicting diffuse solar radiation globally as a result of the availability of reliable measured global solar radiation in most stations around the globe and extraterrestrial solar radiation can be calculated theoretically as given in equation (3). This model pioneered by Liu and Jordan [11] has been applied by several researchers for estimating diffuse solar radiation for several locations across the globe by determining the empirical constants by applying meteorological parameters of their chosen site of interest. Apart from Liu and Jordan [11], those fitted by Page [55] and Iqbal [56] seem to be universally applicable. However, models fitted by numerous researches in Africa [34, 37-39, 57-60] yielded better performance and high accuracy in the fitted sites as compared to reported models in literature that seem to be universally applicable. This result is in agreement with the report in most African countries [33, 43-44, 59, 61-64] confirming that diffuse solar radiation is dependent on the local climate and geographical information of a given site.

Other meteorological parameter-based models are recorded to predict diffuse solar radiation with high precision but most of their input parameters are not really available at most sites of interest in North-Western Africa and across the globe.

In this review, the researchers included two meteorological parameters often applied by one solar energy researcher to predicting solar radiation in Nigeria via: global solar radiation-based models and monthly mean based models. In general, one hundred and eighty-eight (188) theoretical models were reported with 33 functional forms and 20 groups (sub-class) in this review. Eighty three (83) models with the corresponding 8 functional forms and 6 groups were recorded from clearness index-based models representing 44.14 %, 45 models with the corresponding 6 functional forms and 3 groups resulting to 23.93 % were applied for sunshine-based models; 7 models with 1 functional form and 1 group amounting to 3.72 %, for cloud cover-based models; 1 model with 1 functional form and 1 group yielding to 0.53 % for extraterrestrial solar radiation-based models and monthly-based models; and 51 models with 16 functional functions and 8 groups resulting to 27.12 % for hybrid parameter-based models as presented in Fig. 8.

Peers and researchers have shown that it is humanly impossible for now to introduce a set of input variables with a particular functional form for optimal prediction of diffuse solar radiation in Nigeria and Egypt or any other geographical environment across the globe because of its dependence on geographical information and local climate of the site [10, 39-40, 41, 45-46, 52, 57-59, 62-64]. To restate this, a brief review of the efforts of researchers in North-Western Africa to enhance the accuracy of prediction of diffuse solar radiation is presented in the following paragraphs.

El-Sebaili and Trabea [41] employed sunshine-based model and clearness index-based model for predictions of diffuse solar radiation on the horizontal surface for four

Egyptian locations. The selected locations include Matruth, Al-Arish, Rafah and Aswan to represent the weather conditions of the North and South of Egypt. The first, second and third order correlations between the diffuse fraction and clearness index produced better accurate results compared to the correlations between sunshine fraction and diffuse fraction or diffuse coefficients in the selected four locations as shown in Table 1.

Table 1. Statistical indicators for Matruth, Ratah and Aswan El-Sebaai and Trabea [41]

Stations	Degree of Correlation	Correlation between	MBE	RMSE	MPE (%)
Matruth	First	H_d/H and H/H_o	0.07	0.022	1.17
	Second	H_d/H and H/H_o	0.007	0.024	-1.05
	Third	H_d/H and H/H_o	0.006	0.020	-1.07
	First	H_d/H and S/S_o	-0.001	0.003	-0.63
	Second	H_d/H and S/S_o	0.001	0.002	-0.38
	Third	H_d/H and S/S_o	0.001	0.002	-0.39
	First	H_d/H_o and S/S_o	0.003	0.007	-0.72
	Second	H_d/H_o and S/S_o	0.002	0.001	-0.40
	Third	H_d/H_o and S/S_o	0.002	0.001	-0.39
Al-Arish	First	H_d/H and H/H_o	-0.005	0.019	-1.27
	Second	H_d/H and H/H_o	-0.005	0.019	-1.07
	Third	H_d/H and H/H_o		Very poor fitting	
	First	H_d/H and S/S_o	0.002	0.008	-1.26
	Second	H_d/H and S/S_o	0.001	0.002	-0.40
	Third	H_d/H and S/S_o	0.005	0.018	-0.83
	First	H_d/H_o and S/S_o	-0.004	0.015	-1.08
	Second	H_d/H_o and S/S_o	-0.003	0.009	-0.73
	Third	H_d/H_o and S/S_o	0.003	0.009	-0.54
Rafah	First	H_d/H and H/H_o	-0.003	0.010	-0.57
	Second	H_d/H and H/H_o	-0.003	0.010	-0.38
	Third	H_d/H and H/H_o	-0.003	0.011	-0.55
	First	H_d/H and S/S_o	-0.002	0.001	-0.36
	Second	H_d/H and S/S_o	0.003	0.012	-0.16
	Third	H_d/H and S/S_o	0.005	0.016	0.46
	First	H_d/H_o and S/S_o	-0.004	0.014	-0.16
	Second	H_d/H_o and S/S_o	0.001	0.001	-0.12
	Third	H_d/H_o and S/S_o	-0.001	0.001	-0.09
Aswan	First	H_d/H and H/H_o	-0.003	0.014	-1.07
	Second	H_d/H and H/H_o	-0.005	0.012	-0.82
	Third	H_d/H and H/H_o	-0.004	0.015	-0.93
	First	H_d/H and S/S_o	-0.002	0.008	-0.43
	Second	H_d/H and S/S_o	-0.003	0.005	-0.40
	Third	H_d/H and S/S_o	-0.003	0.0114	-0.38
	First	H_d/H_o and S/S_o	-0.001	0.005	-0.27
	Second	H_d/H_o and S/S_o	-0.002	0.005	-0.25
	Third	H_d/H_o and S/S_o	-0.002	0.008	-0.23

Sanusi and Abisoye [47] applied Page model (first order polynomial equation), Liu and Jordan model (third order polynomial equation), second order polynomial, power and exponential models to develop an empirical model for Lagos using eleven years (1999 – 2009) data. The performances for the models were tested using statistical indicators such as Mean Percentage Error (MPE), Mean Bias Error (MBE), Root Mean Square Error (RMSE) and coefficient determination (R^2). The results revealed that the second-order quadratic model yielded reasonably high degree of precision in the forecast of monthly

mean daily diffuse solar radiation in the horizontal surfaces as shown in Table 2. These results were in agreement with the findings in literature [41, 45-46, 57, 64].

Table 2. Statistical indication for the models. Sanusi and Abisoye [47]

Models	MPE (%)	RMSE (MJm ⁻² day ⁻¹)	MBE (MJm ⁻² day ⁻¹)	Coefficient of Determination (R ²)
Page (1961) (First order polynomial)	4.800	0.129	0.104	0.982
Liu and Jordan (1960) (Third order polynomial)	9.336	0.201	-0.194	0.978
Second-order polynomial	0.010	0.048	0.001	0.982
Exponential	0.012	0.051	-0.001	0.980
Power	0.168	0.065	-0.006	0.971

Okundamiya *et al.* [45] calibrated Okundaniya and Nzeako [46] model for numerous numbers of sites, with varying meteorology covering the entire geographical zones in Nigeria. The authors tested the performance of the newly calibrated multivariable regression model, which uses clearness index and cloud cover as inputs for estimating the monthly daily mean diffuse solar radiation, on a horizontal surface in Nigeria with five existing empirical models, which utilizes the clearness index, cloud cover, relative sunshine duration or the combination of two of these variables as inputs [11, 46, 55, 65-66]. The results revealed that the calibrated multivariable regression model performed better than the other five existing models with a relative percentage error of $\pm 6\%$ over Nigeria as presented in Table 3. These results justify the recommendation made by Munner and Munawwar [67] that the inclusion of cloud cover improves the prediction accuracy of diffuse solar radiation on the horizontal surfaces. This result is also comparable to the report of numerous researchers in Africa [35, 37, 39, 42, 44, 60, 68-69].

Table 3. Validation results of six studies diffuse radiation model for Nigeria based on 22 years' data sets Okundamiya *et al.* [45]

Sites	Error Terms (units)	Page [55]	Liu and Jordan [11]	Butt <i>et al.</i> [65]	Karakoti <i>et al.</i> [66]	Okundamiya and Nzeako[46]	Okundamiya <i>et al.</i> [45]
Sokoto	r	0.9497	0.9461	0.8446	0.8173	0.9521	0.9967
	RMSE (MJ/m ²)	0.4049	0.4219	0.8951	1.0711	0.3966	0.1061
	MBE (MJ/m ²)	-0.1652	-0.1832	0.5307	0.7989	-0.1575	-0.0185
	MABE (MJ/m ²)	0.3261	0.3434	0.6515	0.9239	0.3213	0.0793
Maiduguri	r	0.9470	0.8594	0.9085	0.9246	0.9284	0.9950
	RMSE (MJ/m ²)	0.3976	0.6884	0.7798	0.4401	0.4556	0.1981
	MBE (MJ/m ²)	-0.1506	-0.2523	-0.0831	0.0467	-0.1606	-0.1592
	MABE (MJ/m ²)	0.3269	0.5246	0.7136	0.3557	0.3629	0.1623
Abuja	r	0.9930	0.9951	0.9175	0.9295	0.9937	0.9980
	RMSE (MJ/m ²)	0.1727	0.2427	0.6918	0.5350	0.1802	0.1109
	MBE (MJ/m ²)	-0.0744	-0.1414	0.1298	0.1363	-0.0924	-0.0461
	MABE (MJ/m ²)	0.1182	0.1836	0.5151	0.4277	0.1461	0.1000
Ikeja	r	0.9848	0.9933	0.9307	0.9333	0.9875	0.9951
	RMSE (MJ/m ²)	0.1615	0.1857	0.7551	0.3119	0.1605	0.1098
	MBE (MJ/m ²)	0.0370	0.0662	-0.6056	-0.1614	0.0573	-0.0849
	MABE (MJ/m ²)	0.1395	0.1519	0.6550	0.2568	0.1392	0.0913
Enugu	r	0.9887	0.9890	0.9032	0.8767	0.9887	0.9957
	RMSE (MJ/m ²)	0.1348	0.1282	0.5029	0.4102	0.1289	0.0778
	MBE (MJ/m ²)	-0.0220	-0.0365	0.0973	-0.0216	-0.0237	-0.0030
	MABE (MJ/m ²)	0.1137	0.1018	0.4208	0.3241	0.1113	0.0663
Benin-City	r	0.9869	0.9849	0.9508	0.9360	0.9865	0.9935
	RMSE (MJ/m ²)	0.1537	0.1471	0.5365	0.3942	0.1481	0.1129
	MBE (MJ/m ²)	-0.0599	-0.0781	-0.0262	0.0843	-0.0624	-0.0633
	MABE (MJ/m ²)	0.1197	0.1170	0.4814	0.2932	0.1162	0.0955

From the report of existing studies, it is clear that from above findings that introducing an appropriate set of input for diffuse solar radiation prediction in any geographical site and climatic condition is not a viable work. This could be attributed to

numerous number of required inputs variables, inaccuracies associated with irrelevant variables, difficulty in explaining the model, time consuming task for assembling the needed variable and finally its inability to accept many input variables.

For instant, the Artificial Intelligence (AI) and Computation Intelligence (CI) techniques such as Artificial Neural Network (ANN), machine learning, genetic programming, support vector machine, Adaptive Neural Fuzzy Inference System (ANFIS) and hybrid networks have been widely applied in numerous scientific areas for modeling, estimation, prediction, forecasting and optimization such as Support Vector Machine (SVM) [70-74]; Hybrid network [17, 70-71]; genetic programming [16, 75], Adaptive neural fuzzy inference system [73, 75-77]; and an Automatic Relevance Determination (ARD) methodology Bosch *et al.* [78]; can be adopted for predicting diffuse solar radiation in North-Western Africa. Various applications of artificial neural networks are reported in numerous fields such defense, image impression, mathematics, character recognition, aerospace, neurology, meteorology, economic, electronic nose engineering, machine and psychology (Nwokolo and Ogbulezie [9]. These methods have been adopted for prediction and empirical analysis in market trend forecasting, solar and weather.

Boland and Scott [18] determined the comparison between the empirical models and a fuzzy logic based model to estimate hourly diffuse solar radiation in some locations of Australia. The results revealed that coefficients of determination recorded for the fuzzy logic model are comparable, and in most cases more suitable than those of empirical models.

Jiang [19] developed a model based Artificial Neural Network (ANN) model to predict monthly mean daily diffuse solar radiation in China. The researcher employed measured data of eight typical stations for training and data of one station for testing. He proceeded by comparing the estimation of ANN model with those of regression models. According to the author, the results revealed that ANN model compared to the regression model offer is more suitable for estimating diffuse solar radiation in the eight stations studied.

Elminir *et al.* [13] estimated hourly and daily diffuse radiation of Egypt by applying neural network (ANN) and compared the result with two linear empirical models. The performances of the models were determined on the basis of the Mean Bias Error (MBE), Root Mean Square Error (RMSE) and correlation coefficient (r) between the estimated and measured data. The results reveal that ANN model is more suitable to predict diffuse radiation in hourly and daily scales than empirical models.

Alam *et al.* [20] employed Artificial Neural Network (ANN) to estimate monthly mean hourly and daily diffuse radiation in ten Indian stations with diverse weather conditions. They applied different parameter as inputs and used the feedforward back-propagation algorithm to train the ANN model. They discovered that that ANN model compared to the regression model offer is more suitable for estimating diffuse solar radiation in the ten stations studied.

Lazarevska and Trpovski [21] applied neuro fuzzy inference system with a relevance vector machine mechanism for estimation of diffuse solar radiation. They used global solar radiation and solar elevation angle as input parameters to estimate the diffuse solar radiation. Their result revealed that the new developed technique is really effective and remarkably outperformed the existing regression models.

Soares *et al.* [14] stimulated a technique based upon artificial neural network (MLP-ANN) method for estimation of hourly diffuse solar radiation in the city of Sao Paulo, Brazil. The result revealed that the estimated diffuse solar radiation values obtained from

MLP-ANN technique are more suitable compared to those of empirical models as shown in Table 4 and Fig. 3-4.

Table 4. Model Statistics Soares *et al.* [14]

	Sample size	MBE (MJm^{-2})	RMSE (MJm^{-2})	t_s	t_c
Correlation model form Oliveira <i>et al.</i> (2002)	15258	-0.0169	0.193	11.16	1.96
MLP neural-network - Experiment I	2928	0.0116	0.121	5.19	1.96
MLP neural-network - Experiment II	2928	0.0291	0.152	10.63	1.96
MLP neural-network - Experiment III	2928	0.0110	0.155	3.86	1.96

t_c is given at a level of confidence of 95 %.

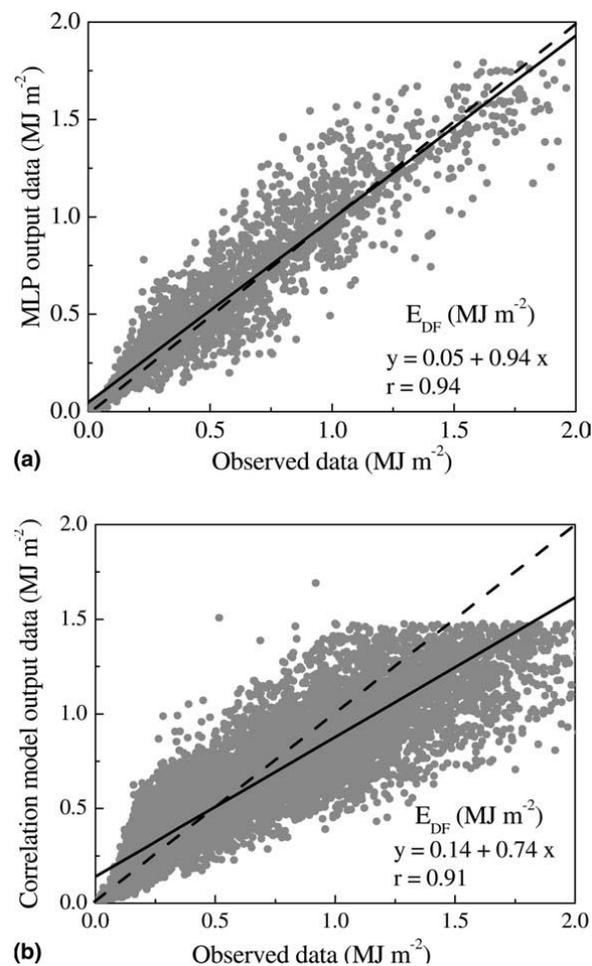


Fig. 3. Dispersion diagram between the hourly values of diffuse radiation observed and (a) using MLP based on 2928 pairs of points and (b) using the correlation model based on 15,258 pairs of points (from Oliveira *et al.* [79]). Dashed line corresponds to diagonal and continuous line corresponds to curve fitted by least squares method. The corresponding linear equations are indicated in the bottom of each diagram and r is the correlation coefficient Soares *et al.* [14].

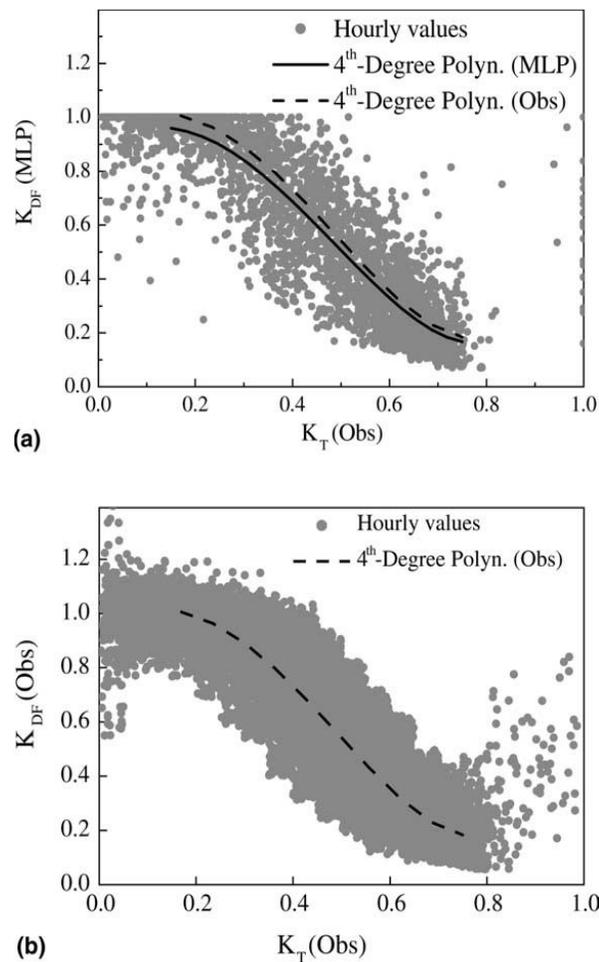


Fig. 4. K_T scatter diagram for hourly values of solar radiation. (a) KDF obtained using MLP, based on 2928 pairs of points and (b) KDF observed in São Paulo City, based on 15,258 pairs of points (from Oliveira *et al.* [79]). The continuous and dashed lines display the fourth-degree polynomial curves obtained, respectively, from MLP and Lawrence (1991); Soares *et al.* [14].

Lou *et al.* [15] employed machine learning algorithm to estimate the horizontal sky-diffuse irradiance and conduct sensitivity analysis for the meteorological parameters. Apart from the clearness index, the authors discovered that predictors including solar attitude, air temperature, cloud cover and visibility are more suitable for estimating diffuse solar radiation component. The Mean Absolute Error (MAE) of the logistic regression using the aforementioned predictors was less than 21.5 w/m^3 and 30 w/m^3 for Hong Kong and Denver, USA as presented in Table 5.

Table 5. Results of Logistic Regression Lou *et al.* [15]

Regression	Predictors	Parameters						Performance			
		f ₀	f ₁	f ₂	f ₃	f ₄	f ₅	Data of 2008-2012		Data of 2013	
								MAE (W/m ²)	R ²	MAE (W/m ²)	R ²
1	k _t	-4.61	7.78	0	0	0	0	29.2	0.850	27.5	0.851
2	k _t , μ	-4.42	8.75	-1.16	.0	0	0	26.3	0.867	26.2	0.851
3	k _t , μ, T _a	-4.37	8.85	-1.38	0.12	0	0	25.7	0.875	25.2	0.866
4	k _t , μ, T _a , Cld	-3.4	7.4	0.8	0.2	-1	0	23.2	0.400	21.8	0.901
5	k _t , μ, T _a , Cld, VIS	-3.3	7.14	0.68	0.13	-1.08	0.18	21.5	0.914	20.0	0.916

Where K_t is clearness index, μ is the sine of solar attitude angle ($\sin(\alpha_s)$), T_a is air temperature, Cld is the cloud amount, VIS is the visibility

Feng *et al.* [12] proposed four artificial intelligence models including the Extreme Learning Machines (ELM), back propagation neural networks optimized by Genetic Algorithm (GANN) Random Forest (RF), and Generalized Regression Neural Networks (GRNN) for estimating daily diffuse solar radiation at two meteorological stations of North China Plain. Daily global solar radiation and sunshine duration were selected as model inputs to train the models. The proposed models were compared with the empirical Iqbal model to test their performance employing measured daily diffuse solar radiation data. The result revealed that the ELM, GANN, RF, and GRNN models all performed much better than the empirical Iqbal model for estimating daily diffuse solar radiation. On the whole, all the models under-estimated daily diffuse solar radiation for both stations with average relative error ranging from 5.8% to 5.4% for all models and 19.1% for Iqbal model in Beijing; 5.9% to 4.3% and 26.9% in Zhengzhou respectively. Generally, GANN model recorded the best accuracy and ELM ranked the next, followed by RF and GRNN model. The ELM model reported a slightly poorer performance but the highest computation speed, and both GANN and ELM could be highly recommended for estimating daily diffuse solar radiation in North China Plain as presented in Table 6 and Fig. 5.

Table 6: Statistics Performances of different models in estimation daily diffuse solar radiation for each Station Feng *et al.* [12]

Station	Model	RRMSE (%)	MAE (MJm ⁻² day ⁻¹)	NS
Beijing	ELM	17.3	0.760	0.908
	GANN	17.1	0.748	0.909
	RF	18.3	0.841	0.897
	GRNN	19.2	0.951	0.880
	Iqbal	32.9	0.162	0.666
Zhengzhou	ELM	13.4	0.762	0.924
	GANN	13.4	0.749	0.928
	RF	15.0	0.862	0.910
	GRNN	16.5	0.997	0.892
	Iqbal	35.8	2.359	0.491

RRMSE is the relative root mean square error, MAE is the mean absolute error and NS is Nash Sutcliffe coefficient

Mohammadi *et al.* [16] applied Adaptive Neuro-Fuzzy Influence System (ANFIS) to select the most influential parameters for prediction of daily horizontal diffuse solar radiation (H_d). Ten significant parameters are selected to analyze their impact on estimation H_d in the city of Kerman, situated in the south central part of Iran. For this purpose, a thorough parameter selection was conducted for the cases with 1, 2 and 3 inputs to introduce the best and worst inputs combinations. For the cases with 2 and 3 inputs, 45 and

120 possible combinations of inputs are considered, respectively. For the cases with one input variable, the results revealed that sunshine duration(s) is the most influential variable. Moreover, combination of H, H_o and S are the best sets among the cases with 2 and 3 inputs variables respectively. The observed result revealed that combinations of either 2 or 3 most relevant inputs would be appropriate to provide a balance between the simplicity and high precision. Predictions using the most influential set of 2 and 3 inputs revealed that for the ANFIS model with two inputs variables, the mean absolute percentage error, mean absolute bias error, root mean square error and correlation coefficient are 23.0579%, 1.0176 MJ/m², 1.3052 MJ/m² and 0.8247, respectively, and for the ANFIS model with three inputs they are 18.3143%, 0.8134 MJ/m², 1.1036MJ/m² and 0.8783, respectively as presented in Table 7 and Fig. 6.

Table 7. Five most and least relevant combination of inputs and ANFIS regression error (RMSE in MJ/m²) achieved for training and checking phases Mohammadi *et al.* [16].

Combination No.	Combination of Inputs	RMSE for Training	RMSE for Checking
Combination 1	H, H _o , S (1st best model)	1.2417	1.2889
Combination 9	H, S, and S _o (2 nd best model)	1.2523	1.2968
Combination 15	H, S, and (3rd best model)	1.2532	1.2971
Combination 5	H, H _o and T _{arg} (4th best model)	1.2820	1.2925
Combination 3	H, H _o , and T _{min} (5th best model)	1.2902	1.3222
Combination 28	H, T _{max} and RH (1st worst model)	1.8916	1.9339
Combination 90	S _o , T _{min} and S (2 nd worst model)	1.8671	1.8673
Combination 97	S _o , T _{avg} and S (3rd worst model)	1.8571	1.8643
Combination 94	S _o , T _{max} and S (4th worst model)	1.8395	1.8585
Combination 117	T _{ava} , RH and V _p (5th worst model)	1.8231	1.8890

Where S is the sunshine duration, H global solar radiation, δ solar declination, H_o extraterrestrial solar radiation S_o maximum possible sunshine duration V_p water vapour pressure, RH relative humidity, T_{avg} average air temperature, T_{min} minimum temperature, T_{max} maximum temperature.

During the last decades, numerous renewable energy researchers have carried out number of studies for estimation of diffuse solar radiation mainly by developing different soft computing techniques and regression models, but there is still a main challenge regarding the development of powerful hybrid soft computing techniques and models with high level of reliability and adaptability to achieve accurate predictions just as hybrid regression models offer more suitable prediction compared to one parameter-based models. Lately, coupling different approaches of soft computing to build a hybrid model has received a considerable attention in the renewable energy area. On the whole, it is possible to take the advantage of specific nature of different soft computing techniques for enhancing the precision. In fact, the particular features of different soft computing techniques are able to capture different patterns in the data series. Recent findings from literature have revealed that hybrid soft computing approaches would be particularly effective and promising for different applications of renewable energy to enhance the estimation accuracy and reliability.

For instance, in a study to determine diffuse solar radiation in the city of Kerman, Shamshirband *et al.* [81] employed a couple model by integrating the support vector machine (SVM) with Wavelet Transform (WT) algorithm for estimating daily horizontal diffuse solar radiation. In order to test the validity of the coupled SVM-WT method, daily measured global and diffuse solar radiation data sets for city of Kerman located in sunny part of Iran are utilized. Using the developed SVM-WT model diffuse fraction is related

with clearness index as the only input variable. The performance of SVM-WT model is calculated against radial basis function SVM (SVM-RBF), Artificial Neural Network (ANN) and a third order empirical model established by the researchers. The results revealed that the estimated diffuse solar radiation values by the SVM-WT model agreed favourably with measured data. The statistical Indicators revealed that the mean absolute bias error, root mean square error and correlation coefficient are 0.5757 MJm^{-2} , 0.6940 MJ/m^2 and 0.9631 , respectively. While for the SVM-RBF ranked next the attained values are 1.0877 MJm^{-2} , 1.2583 MJ/m^2 and 0.8599 , respectively. In a nut shell, the study revealed that SVM-WT is an efficient method which enjoys much higher precision than other models, especially the third order empirical model as shown in Table 8 and Fig. 7.

Table 8. The attained MABE, RMSE and R for all models for the testing data set Shamshirband *et al.* [81].

Model	MABE (MJ/m^2)	RMSE (MJ/m^2)	R
SVM – WT	0.5757	0.6940	0.9631
SVM – REF	1.0877	1.2583	0.8599
ANN	1.1267	1.3183	0.8392
Empirical Model	1.2171	1.4548	0.8156

The regression models for predicting diffuse solar radiation were examined extensively and its performances were compared with the soft computing approach in North-Western Africa and across the globe. This review paper distinctively provided reliable outcome for various approaches (empirical and soft computing model). The regression models regarded as capable and convenient for hourly, daily and monthly estimation are clearness index-based models, sunshine-base models, cloud cover-based models, extraterrestrial solar radiation-based models, monthly-based models and hybrid parameter-based model. A number of important aspects identified in literature as well as shortcomings with solutions recommended in the present study are summed up subsequently.

In the light of presented review literature, it seems that a number of sites do not have meteorological stations, whereby empirical and soft computing models should be developed employing attitude, latitude, longitude, solar declination angle, and extraterrestrial solar radiation inputs for precise measurement as they require no experimental measurement to obtain their values. Soft computing models have newly been initiated for predicting renewable energy resources, but additional work is needed to enhance solar radiation prediction accuracy pertaining to various seasons, climate change and poor weather, on different surfaces, (*e.g.*, tiled) Nwokolo and Ogbulezie [9]. Hence, according to the authors, the greatest advantages may be needed from natural resources to supply increasingly reliable efficient solar systems in the market.

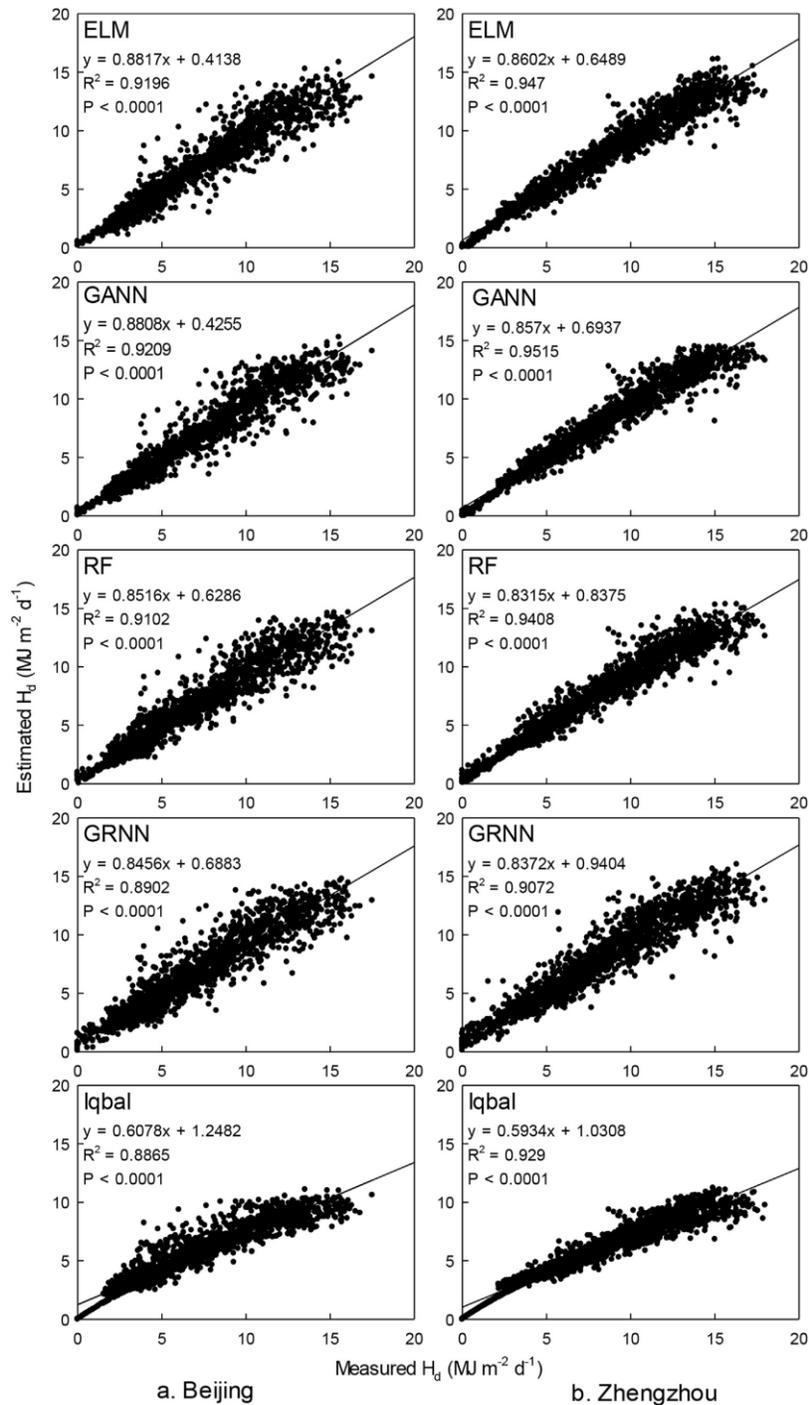


Fig. 5. Scatter plots of the measured versus the estimated daily diffuse solar radiation at (a) Beijing and (b) Zhengzhou of North China Plain by Feng *et al.* [12].

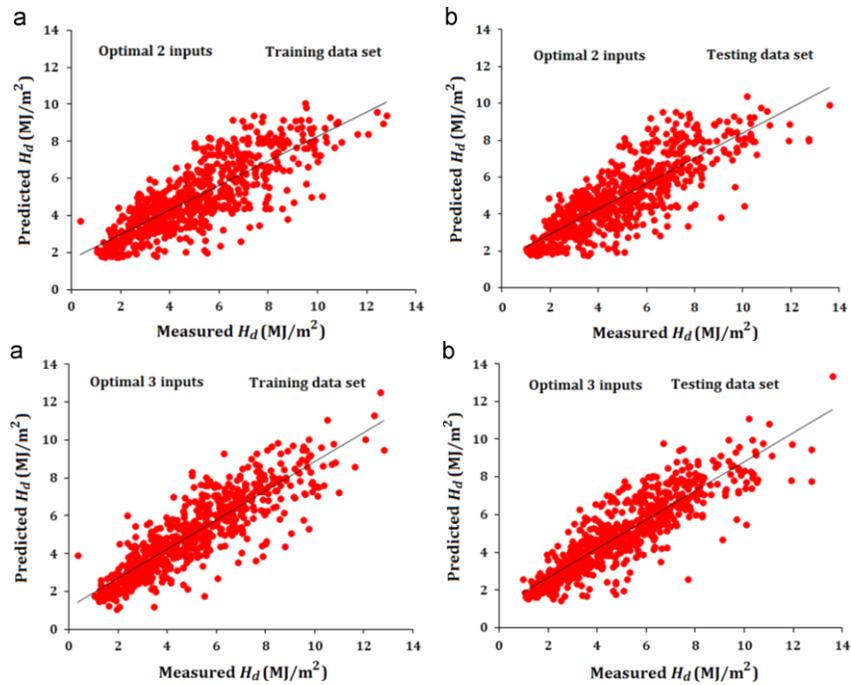


Fig. 6. Performance of the ANFIS model to predict H_d using optimal combination of 3 inputs for: (a) training dataset and (b) checking dataset Mohammadi *et al.* [16].

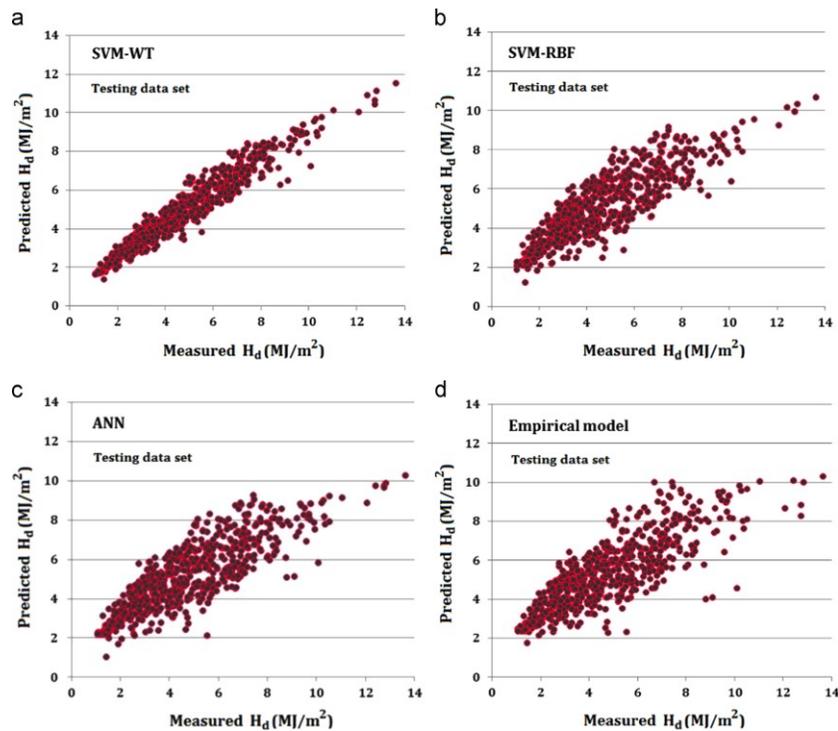


Fig. 7. Scatter plots of them ensured diffuse solar radiation versus predictions of (a) SVM–WT, (b) SVM–RBF, (c) ANN and (d) empirical model for the testing data set (Shamshirband *et al.* [81])

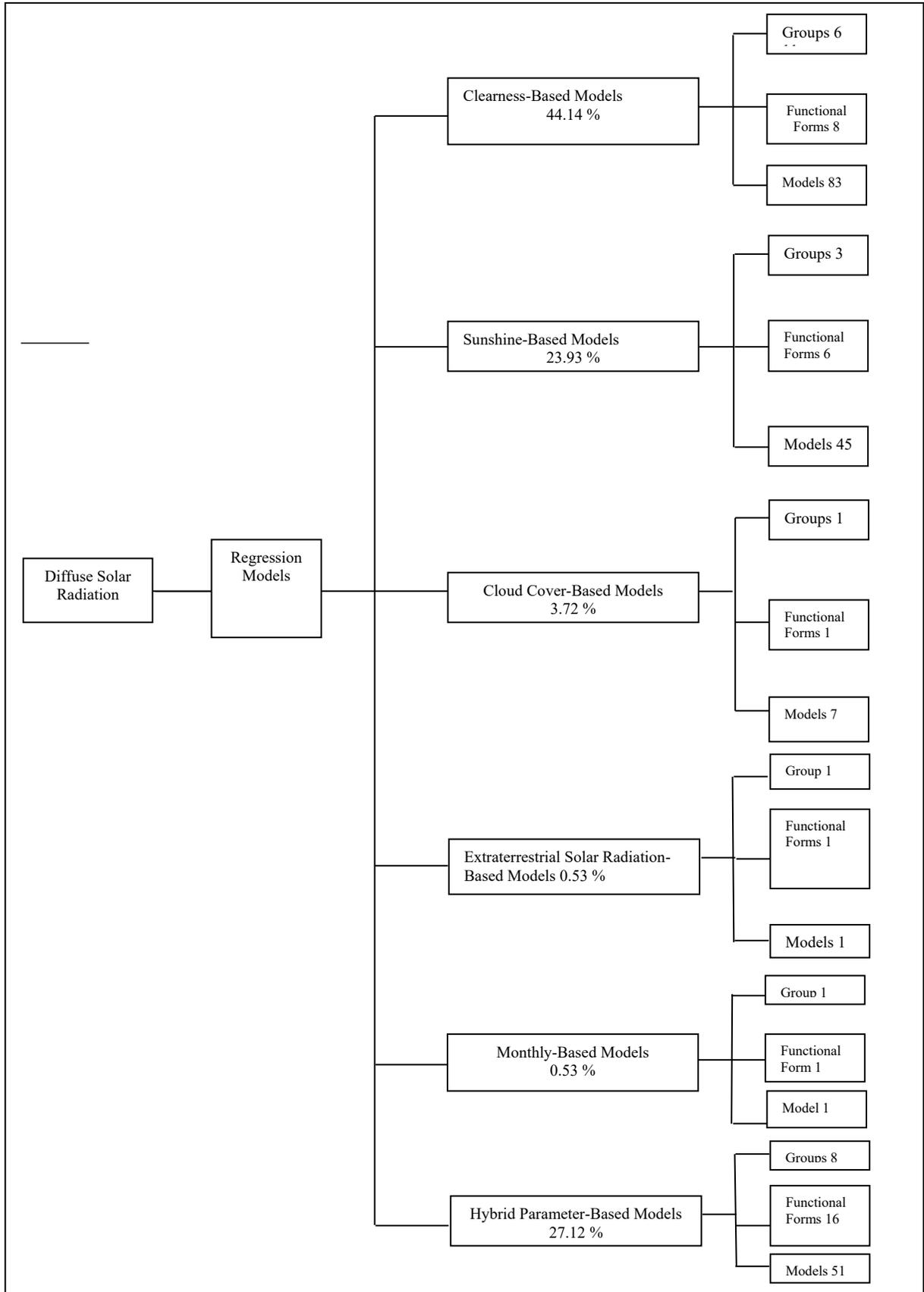


Fig. 8. Classification of diffuse solar radiation and its associated number of groups, functional forms, and models in Nigeria and Egypt

5. Concluding Remarks

The regression models for predicting diffuse solar radiation were investigated extensively and its performances were compared with the soft computing approach in North-Western Africa and across the globe. This review paper distinctively provided reliable outcome for various approaches (regression and soft computing model). The regression models are regarded as capable and convenient for hourly, daily and monthly estimation are clearness index-based models, sunshine-base models, cloud cover-based models, extraterrestrial solar radiation-based models, monthly-based models and hybrid parameter-based model. Owing to the inability of regression models to accept many input parameters but rather strengthened in its reliability, a number studies in literature revealed that soft computing models are more suitable for predicting diffuse solar radiation in several locations distributed across the globe. Thus, applying soft computing and even power hybrid soft computing models will culminate in the greatest understanding of availability diffuse solar radiation in a particular region or location that is needful for supplying increasingly reliable efficient solar systems in the market.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this paper.

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