FORECASTING DIFFUSE SOLAR IRRADIATION

Summary

The majority of research into predicting diffuse solar irradiation has been conducted using contemporaneous values of the clearness index augmented by other predictors. In recent years this research has largely been developed using variants of the Boland-Ridley-Lauret decaying logistic function model. The focus on developing models for prediction of diffuse (or direct) irradiation starting with global horizontal irradiation (GHI) is due to the ease of measuring GHI (or estimating it from satellite images) as compared to the complicated and expensive means of measuring diffuse and direct. Little attention has been directed at developing methods of forecasting diffuse irradiation from previous values of it of clearness index. One approach is given in this paper and alternative approaches will be proposed.

Keywords: Diffuse solar irradiation, global solar irradiation (GHI), forecasting, clearness index, diffuse fraction

1. Introduction

Solar irradiation is comprised of three components, global horizontal irradiation (GHI), diffuse and direct. Direct solar irradiation is the energy coming directly from the sun to a location on the earth, whereas diffuse reaches that location from reflections from particles in the atmosphere. For various applications, either the diffuse or direct component as well as the GHI is needed. In general, only the GHI is measured or inferred from satellite images. Then a separation model is used to estimate the other components. The most prevalent method is to estimate the diffuse fraction d_t (the diffuse divided by the GHI) from the clearness index (the GHI divided by the solar irradiation at the top of the atmosphere at that location) and possibly other predictor variables. What was probably the first attempt at this modelling was Liu and Jordan (1960), and they used a piecewise linear model for the single predictor case. The innovations that were made to the modelling in the next few decades similarly depended on the piecewise linear approach, albeit with extra predictors. Boland et al. (2008) developed a single predictor method but with a decaying logistic form of the model. The focus was on hourly diffuse modelling and Ridley et al. (2010) added several more predictor variables to the same structure, producing the so-called BRL model. One important feature of that model was that it was designed in such a way that the extra predictor variables did not have to be measured, to increase the flexibility of application. They could be calculated but as in the previous approaches, it included values at the same time or even future time steps in the modelling, eliminating the ability for use in forecasting.

The use of the hourly time step averages out a phenomenon that needs to be taken into consideration at shorter time steps, often needing to be considered for system modelling. That is the feature called cloud enhancement. At short time steps like one minute, the sky can be clear directly overhead, but surrounding clouds can increase the total energy through reflection, even increasing the received energy above the value at the top of the atmosphere. Engerer (2015) modelled this effect and Starke et al. (2018) gave a more improved version of the modelling. For these and other works, the BRL model formed the basis for the structure. For a review of the various approaches, Yang (2022) provides a comprehensive examination. In the present work, the BRL model structure is altered to make it suitable for forecasting. The format and data used will be described in Section 2 and results in Section 3.

2. Data and Methods

The data used for the study is from the one minute data that is collected for a small number of stations in Australia by the Bureau of Meteorology (BOM). The data had some gaps and infilling was performed and then accumulated in half hour data simply for testing the methods. In the original BRL model, the predictors apart from the clearness index k_t are apparent solar time (AST), solar altitude, the daily clearness index K_t and a variable called persistence which is the mean of the clearness index for the hour before and after the time of focus. Clearly, for the forecast model, the last two variables can't be used, but neither can k_t. The added predictors are k_{t-1}, k_{t-2} and similar variables for the diffuse fraction, d_{t-1}, d_{t-2}.

3. Results

For comparison, the approaches used are for using the BRL model for Adelaide airport 2016 data as well as the forecast model. Since in this exercise the focus is on seeing how the forecast model works using the only variable that needs to be measured is the GHI, this comparison is sufficient. In further work, the forecast method will be compared to other approaches in the literature. At the moment, none have been found to mirror the task at hand here. Using the BRL model in non-forecast mode for the 2016 data, the results are displayed in Fig 1.

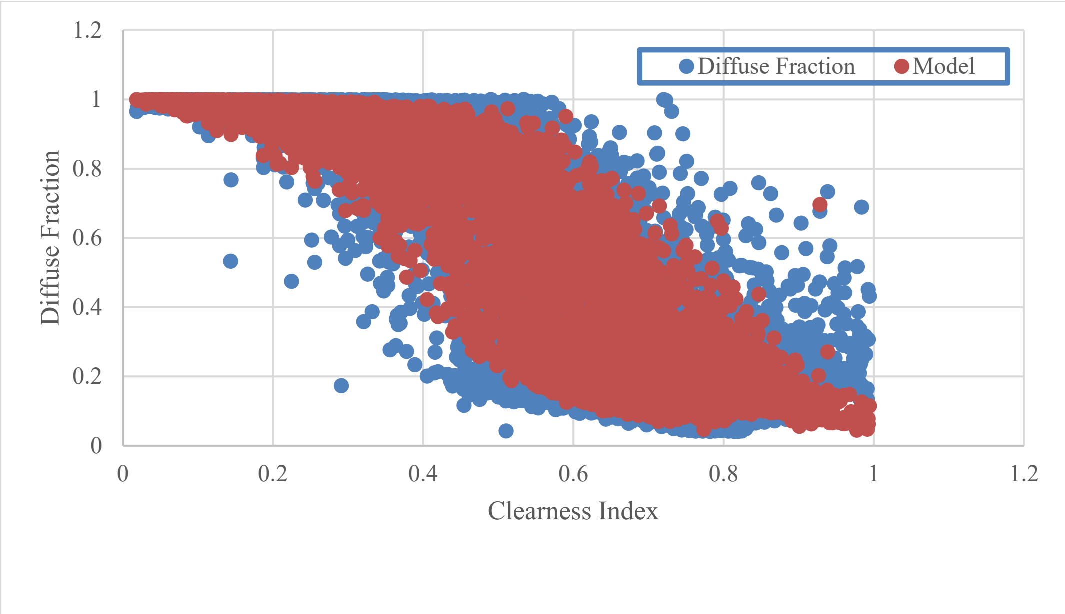

Fig. 1: Adelaide airport diffuse fraction and BRL model

If the model is altered to the forecast mode, the result is the depiction in Fig.2. There are a couple of things to note here. The data itself is displayed differently since the horizontal axis is $\boldsymbol{k_{t-1}}$ rather than $\boldsymbol{k_t}$ as since this a forecast model, the present value of the clearness index is not known. In both situations there is a seemingly good overlap of the data and the model. The definitive measure though is a quantitative one. The Mean Bias Error (MBE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were calculated for each model. The results are given in Table 1.

4. Discussion and Conclusion

The MBE for both models is very low indicating essentially no over or under fitting. The MAE and RMSE for the BRL model are lower than for the forecast model as expected. Using the present value of the clearness index as well as the parameters that account for in essence future values of the clearness index should improve the scores. The error metrics for the forecast model are not excessively large than for the BRL model. There are activities left to be examined. One is a formal time series model for forecasting involving a combined seasonal and Autoregressive Moving Average (ARMA) model. Even that does not take care of the fact that the forecast model should be able to be applied for locations where no diffuse irradiation measurements are available. This will be the focus of further work, using both the regression and time series approaches. It will be a complicated process and may well involve some use of the BRL model to estimate historical values of the diffuse fraction.

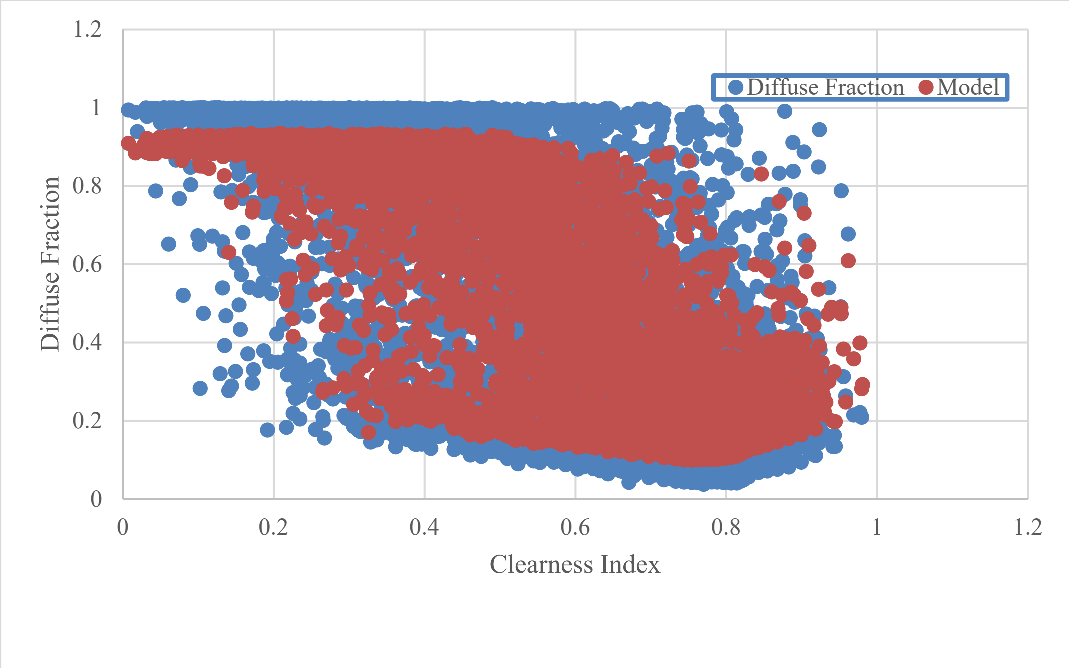

Fig. 2: Adelaide airport diffuse fraction and forecast model

Tab. 1: Error metrics for the BRL and forecast models

Model	MBE	MAE	RMSE
BRL	0,0001	0.079	0.115
Forecast	-0.0007	0.112	0.161

5. References

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