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A Comparative Performance Study of Diffuse Fraction Models Based on Data from Vienna, Austria

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ABSTRACT

Computational applications for the evaluation of buildings' energy performance (including their passive and active solar energy systems) require detailed information regarding incident solar radiation. As only global horizontal irradiance data is available for most locations, models are needed to derive from such global data, the diffuse radiation component. In this context, the present paper compares the predictive performance of six existing and one new diffuse fraction models for the location of Vienna, Austria.

KEYWORDS: Solar radiation, diffuse fraction model, clearness index, global horizontal irradiance, diffuse horizontal irradiance, Sun state.

1 INTRODUCTION

Incident solar radiation has a significant impact on the thermal and visual performance of buildings. Thus, the amount of solar radiation and its diffuse and direct components must be known. Unfortunately, only the global horizontal irradiance is widely measured. Consequently, extensive research has been done to estimate components of global horizontal irradiance. Different models use different input data. Depending on the variables, approaches, and location, different predictive performance is achieved.

In the past, diffuse fraction model developers mainly used clearness index (ratio of global horizontal irradiance over horizontal extraterrestrial irradiance) as a model input to derive the diffuse fraction (ratio of diffuse horizontal irradiance to global horizontal irradiance). Clearness index gives information about the overall sky conditions. Small values denote overcast/dark skies, whereas higher values denote bright (not necessarily clear) skies. Diffuse fraction is generally lower when the clear index value is high. However, at very high clearness index values (higher than around 0.8 for Vienna) diffuse fraction might increase again (unobstructed sun, bright clouds). Clearness index does not yield on its own accurate results for diffuse fraction. Past research has thus involved the deployment of multiple input variables, resulting in rather complex models. Most of these models appear to perform satisfactorily only for locations whose data were used for model development, i.e., mostly northern hemisphere (Spencer 1982, Boland et al. 2001). Recent studies (Dervishi and Mahdavi 2012, Vazifeh et al. 2013) using measured data from Vienna, Austria documented a rather poor performance by the models.

2 METHOD

2.1 Data

Data from the weather station of Building physics and Building ecology department of Vienna University of Technology was used for the present study. This data consists of hourly global and diffuse horizontal irradiance obtained from a sunshine pyranometer (Delta-T 2007). The monitored data was subjected to multiple quality checks. For instance, data for sun altitudes below 5 degrees was removed from the dataset. Moreover, hourly global horizontal irradiance less than 50 $W.m^{-2}$ was excluded. Finally, hourly global horizontal irradiance data measured by sunshine pyranometer was compared with high precision pyranometer (Kipp & Zonen 2004). Thereby, instances where measured values were more than 5% apart were discarded.

2.2 Models description

A brief description of the models (functions, variables) selected for the present study are shown in Table 1. Erbs et al. (1982) presented a piecewise polynomial model, which used only clearness index as a variable. Maxwell (1987), by applying a quasi-physical model, developed a model which used air mass and clearness index as variables. The model is called DISC (Direct Insulation Simulation Code), which generates direct beam irradiance. Reindl et al. (1990) applied four variables, namely clearness index, solar altitude, relative humidity, and temperature in a piecewise function. Skartveit and Olseth (1987) developed a simple hourly model using solar altitude. In subsequent work (Skartveit and Olseth ,1998) they presented a model, which considered surface albedo and variability index. Boland et al. (2001) highlighted the shortcomings of existing models for the southern hemisphere. They developed a logistic model deploying clearness index as a variable. Lauret et al. (2010), by adding more variables to the Bolands' logistic function, improved the model's performance.

All models, including a newly developed model for Vienna (see section 2.3 below), were implemented in the Matlab programming environment (MATLAB 2010). In case of Erbs et al., Reindl et al. and Boland et al. models, applicable coefficients of the models were calibrated, i.e., adjusted to achieve best fit to the empirical observations (Vienna data, 2013). To compute solar altitude, a procedure document in Reda and Andreas 2008 was used.

Table 1 Models overview

Model	Function	Variables
Erbs et al. 1982	Polynomial	k_t
Maxwell 1987	Exponential	k_t, m_{air}
Reindl et al. 1990	Polynomial	k_t, sinα, T, φ
Skartveit and Olseth 1998	Polynomial	k_t, α, σ_3
Boland et al. 2001	Logistic	k_t
Lauret et al. 2010	Logistic	k_t, K_t,AST, α, ψ

2.3 A diffuse fraction model for Vienna

The distribution of clouds significantly affects the magnitude of solar radiation reaching the building surface. A normal weather station does not give information about cloud cover and distribution. Consequently, simple diffuse fraction models must rely on standard variables such as temperature, humidity, and global horizontal irradiance. A potential relationship between such variables and the diffuse fraction may be captured via statistical analysis of the measured data. With regard to Vienna data, we noticed that the correlation between clearness index and diffuse fraction can be improved, if multiple discrete ranges of global horizontal irradiance are differentiated. Therefore, for each bin of global horizontal irradiance, linear least square regression was employed to fit the model to the data (observed values of diffuse fraction for the Vienna location in the year 2013). From 14 initial variables, six promising ones were selected. These variables are clearness index, daily clearness index (average of hourly clearness index day), solar altitude, relative humidity, temperature, and sun state. Sun state is a boolean variable: It equals to one in case of unobstructed sun, otherwise it is zero. Sun state and clearness index have the highest impact on diffuse fraction. Sun state data was imported from the pyranometer. The selected variables and their definitions are given in Table 2.

The coefficients derived from least square regression are included in Table 3. Note that the values of temperature and relative humidity had a rather limited influence on the resulting diffuse fraction results.

Table 2 Variables being used in the present paper model

Variable	**Symbol**	**Formulation**
Solar altitude	α	$(\frac{\alpha}{90})^{6.7}$
Clearness index	k_t	$(1-k_t)^{0.8}$
Daily clearness index	K_t	$(1-K_t)^{0.5}$
Temperature	*T*	$(1-\frac{(T+20)}{70})^{1.8}$
Relative humidity	*RH*	*RH/100*
Sun state	*SS*	*SS*

Table 3 Coefficients for the proposed Vienna model as a function of the global horizontal irradiance (GHI) range

	0<GHI<100	100<GHI<200	200<GHI<300	300<GHI<400	400<GHI<500	500<GHI<600	600<GHI<700	700<GHI<800	800<GHI<900	900<GHI<1000
1	0.88	0.796	0.487	0.535	0.098	0.392	0.442	0.526	0.329	2.97
SS	-0.39	-0.529	-0.53	-0.574	-0.47	-0.632	-0.644	-0.649	-0.742	-2.325
α	0.33	0.349	-0.45	-0.244	-0.561	-1.27	-0.755	0.192	-0.011	-0.484
k_t	-0.004	-0.089	0.193	0.118	0.453	0.287	0.162	-0.174	0.502	-1.365
K_t	0.044	0.231	0.331	0.37	0.566	0.387	0.496	0.451	0.610	-0.199
T	0.071	0.018	0.075	0.067	0.198	0.22	0.079	0.049	0.136	-0.562
RH	-0.001	0.0257	0.035	0.0018	0.071	0.115	0.077	0.2076	0.0794	0.407

2.4 Evaluation criteria

A number of statistical measures (see equations 1 to 6) were used in order to evaluate the performance of the models, namely Median of the absolute percentage error (MeAPE), Median of the bias error (MeBE), Root mean square error (RMSE), Mean bias error (MBE), Mean absolute error (MAE), and Coefficient of variation of RMSE (CV_{RMSE}).

$$MeAPE = median(|\frac{I_d - I_{msrd}}{I_{msrd}} \times 100|) \quad (1)$$

$$MeBE = median(\frac{I_d - I_{msrd}}{I_{msrd}}) \times 100 \quad (2)$$

$$MBE = \frac{\sum_{i=1}^{n}(I_d - I_{msrd})}{n} \quad (3)$$

$$MAE = \frac{\sum_{i=1}^{n}(|I_d - I_{msrd}|)}{n} \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(I_d - I_{msrd})^2}{n}} \quad (5)$$

$$CV_{RMSE} = \frac{RMSE}{\bar{I}_{msrd}} \times 100 \quad (6)$$

Here, I_d, I_{msrd} are predicted diffuse horizontal irradiance and measured diffuse hoizontal irradiance respectively.

In addition to the above statistics, the percentage of results with a specific Relative Error (RE) range was displayed in terms of a cumulative distribution function (CDF). This function demonstrates the percentage of the results, which fall within a certain relative error range.

3 RESULTS AND DISCUSSION

Figure 1 shows the value of the selected statistics for all models both for the year 2013 (whose data was used for model calibration) and 2011 (whose data was used solely for model verification. Figure 2 shows the cumulative distribution function (percentage of results with a specific Relative Error) for all models depicted for 2013 (left) and 2011 (right) data. As these Figures suggest, the Vienna model generally performs best. Whereas in the case of the Vienna model roughly 80% of the results show RE values less than 20%, only about 60% of the results of other models display the same error level.

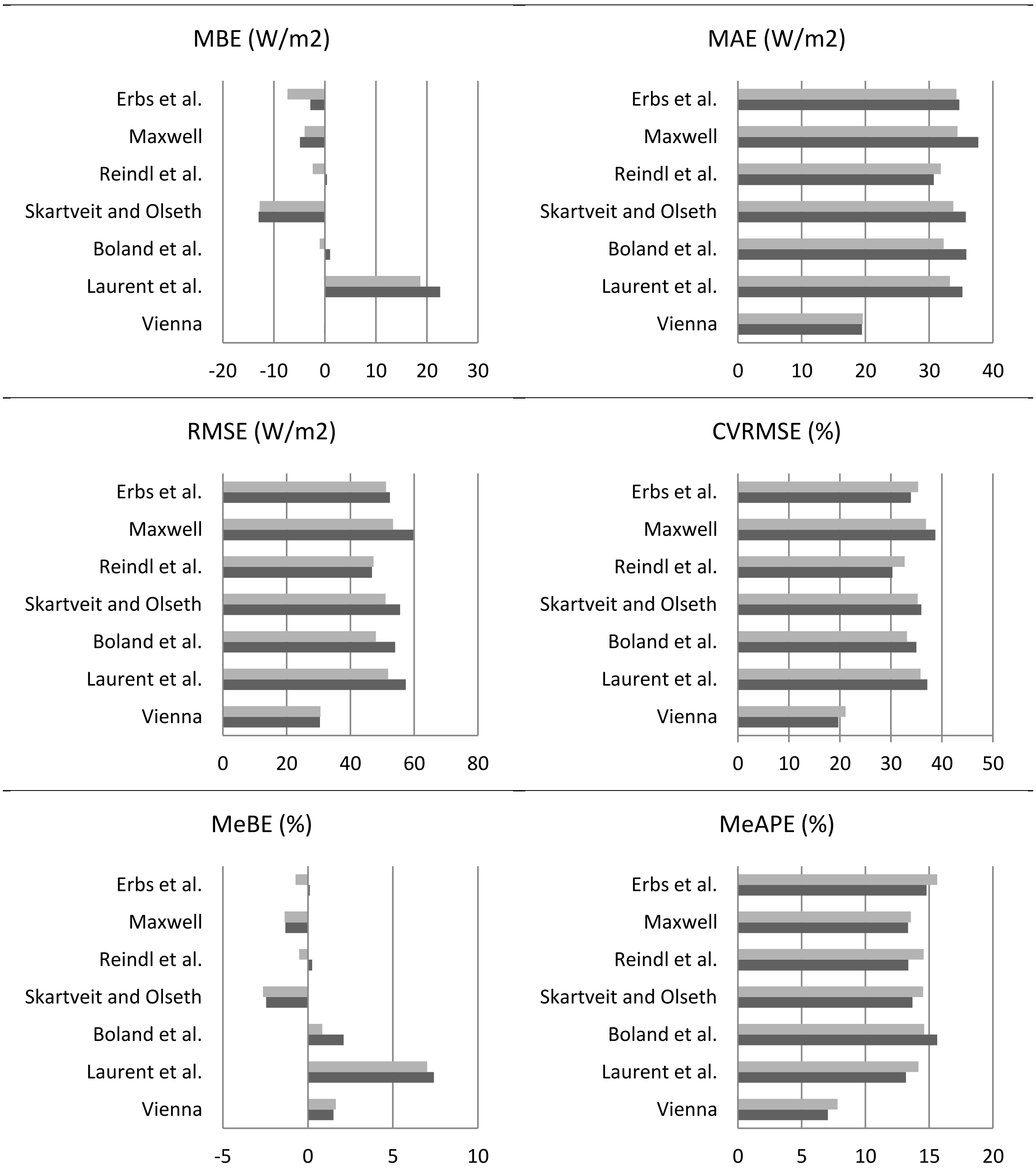

Figure 1: Comparison of the models in terms of various statistics for the calibration (2013, white bars) and verification (2011, dark bars) periods.

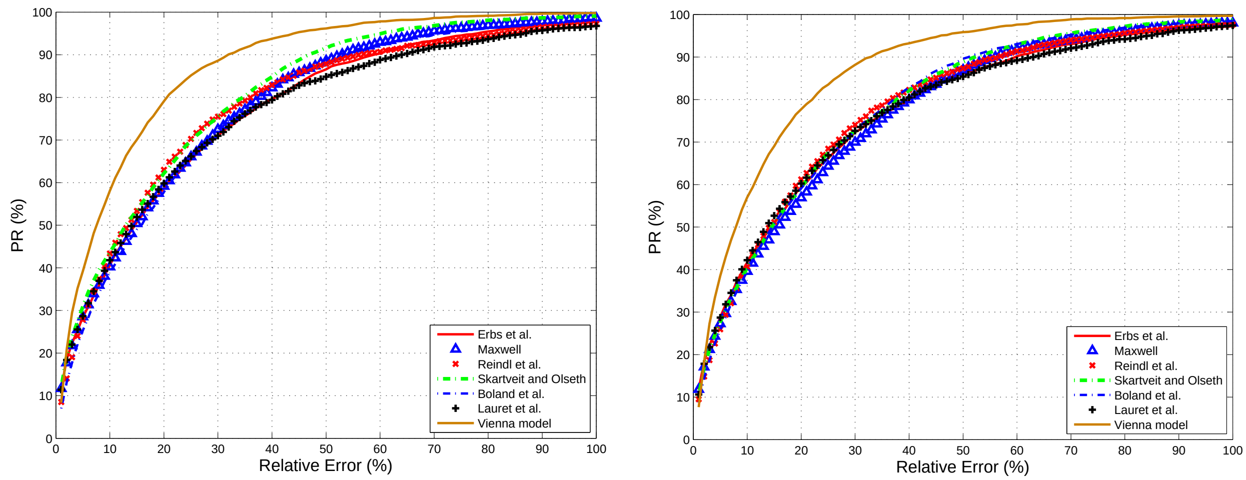

Figure 2: The cumulative distribution function (CDF) of the relative errors for all models for the calibration (Left: 2013 data) and verification (Right: 2011 data) periods.

4 CONCLUSION

The performance of six existing diffuse fraction models was assessed using data collected in Vienna, Austria. In case of three of these models, applicable coefficients were calibrated (using data from 2013) to achieve the best possible fit to the empirical data. Nonetheless, none of these models displayed a satisfactory performance when their predictions were evaluated against observed data from 2011. In about 60% of the cases, the RE values were above 20%. A newly developed detailed empirically-based model for Vienna performed significantly better. However, the performance of this model has not been assessed for data from other locations. Ongoing and future research shall further explore the potential for development of models that could satisfy the twofold criteria of wide geographic applicability and acceptable accuracy.

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