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Evaluation of regression and neural network models for solar forecasting over different short-term horizons

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Forecasting solar irradiation has acquired immense importance in view of the exponential increase in the number of solar photovoltaic (PV) system installations. In this article, analyses results involving statistical and machine-learning techniques to predict solar irradiation for different forecasting horizons are reported. Yearlong typical meteorological year 3 (TMY3) datasets from three cities in the United States with different climatic conditions have been used in this analysis. A simple forecast approach that assumes consecutive days to be identical serves as a baseline model to compare forecasting alternatives. To account for seasonal variability and to capture short-term fluctuations, different variants of the lagged moving average (LMX) model with cloud cover as the input variable are evaluated. Finally, the proposed LMX model is evaluated against an artificial neural network (ANN) model. How the one-hour and 24-hour models can be used in conjunction to predict different short-term rolling horizons is discussed, and this joint application is illustrated for a four-hour rolling horizon forecast scheme. Finally, the effect of using predicted cloud cover values, instead of measured ones, on the accuracy of the models is assessed. Results show that LMX models do not degrade in forecast accuracy if models are trained with the forecast cloud cover data.

Introduction

Rapid and accelerating growth of solar photovoltaic (PV) power installations as a source of renewable energy calls for accurate forecasting of power output. This, in turn, requires forecasting of variables such as solar radiation and ambient temperature, which directly affect the power output of a solar system.

The value of solar forecasting for large electric grids has been studied by Martinez-Anido et al. (2016), who also investigated the effect of prediction uncertainty on unit commitment scheduling decisions for power plants with different start-up and shut-down times. They emphasize the need to have solar and PV forecast (a) one hour ahead or less (for gas turbines and internal combustion engines), (b) a few hours ahead for gas combined cycles as well as gas/oil steam turbines, and (c) one day ahead for nuclear, biomass, and coal plants. This forecasting capability is also required for proper unit commitment/scheduling, control and power dispatch planning of distributed generation systems for communities with large solar penetration, as well as large individual buildings with multiple energy sources (combined heat and power, solar PV), which include thermal and battery storage subsystems and variable electric and gas rates. A report by Letendre et al. (2014) reviews solar forecasting approaches and describes how they are being used by grid operators, utility companies, and other market participants for planning and operations.

The current thinking (Kleissl 2013) is that (a) for very short term (<30 min), the use of ground-to-sky imagers to capture cloud-positioning information and convert that into deterministic models is the most appropriate approach; (b) for short time horizons (less than two hours), statistical forecasting methods are the most attractive; (c) for two- to six-hour time horizons, a combination of methods that relies on observations or predictions of cloud cover through numerical weather prediction models and cloud-vector information is the best; and (d) for longer time horizons (greater than six hours) physics-based models should typically be employed.

For the purposes of this study, we define one hour as the *forecasting period*, in other words, the basic unit of time for which forecasts are to be made. The *forecasting horizon* is the number of periods into the future covered by the forecast.

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If the forecasts can be revised at each time period using the most recent period's value and other current information, and if the horizon is always of the same length, this situation is called a *moving (or receding) horizon* analysis. In this study, we use one hour as the forecasting period, 24 hours as the forecasting horizon, and moving horizons have been considered at both one-hour and four-hour intervals. The objectives of this article are to report on analyses conducted into modeling approaches and expected uncertainties of hourly irradiation forecasts for 24-hour and one-hour horizons under (a) ex ante conditional forecasting with an exogenous variable such as cloud cover and (b) ex ante unconditional forecasting when cloud cover itself must be provided by a commercial weather service provider. Also, we propose an algorithm that allows the one-hour rolling and 24-hour hourly predictions to be suitably combined into a four-hour rolling horizon forecast scheme. The article begins with a relevant literature review followed by a description of the datasets used. The various model forms are then presented. Following sections then present and discuss analysis results of one-hour rolling horizon and four-hour forecast models, respectively, using measured cloud cover data. Next, we address the issue of model forecast accuracy when the cloud cover variable is itself a forecasted value subject to some degree of uncertainty. The final section concludes with a summary of findings.

Literature review

Following the early work by Goh and Tan (1977), modeling and forecasting of solar irradiation has been the focus of numerous studies in the past few decades; only the most relevant studies are briefly reviewed here. For a comprehensive review of application of artificial intelligence (AI) methods in solar PV systems, one can refer to the work by Mellit and colleagues (Mellit 2008; Mellit and Soteris 2008), which concluded that AI methods are of great interest because they need less computational effort and do not require knowledge of internal system parameters. A review paper by Inman et. al (2013) categorized the methods used for developing solar forecasting models into regression methods, time series, artificial neural networks (ANNs), and other methods, and under each category they briefly discussed basic ideas and reviewed the relevant literature. The work by Antonanzas et al. (2016) is another recent and useful review that classifies and discusses different methods applicable to solar power forecasting. They point out that while most studies in the area have focused on one-day-ahead forecasting horizons, this range is likely to change as the energy market evolves and intrahour trading becomes important. They add that statistical models are more often used and have proven to be more efficient than parametric methods.

Yadav and Chandel (2014) also reviewed the work on using ANNs to predict solar radiation. They point out that ANNs predict solar radiation more accurately than conventional methods but that their performance is rather sensitive to the input variables used. Qazi et al. (2015) also reviewed the current literature on application of ANNs in solar forecasting. They found that prediction performance of neural networks is dependent on proper choice of input parameters, as well as on architecture type and training algorithm selected. Sfetsos and Coonick (2000) evaluated two different types of ANNs: The relative performances of the multilayer perceptron (MLP) and the radial basis function (RBF) are compared to those of conventional methods based on atmospheric clearness index, and ANNs were found to be superior. Similarly, Dorvlo et al. (2002) used MLP and RBF to predict the atmospheric clearness index. After training and testing both models using historical data from Oman and comparing their performances, they concluded that models give similar performance results but RBF needs less computation time. Behrang et al. (2010) investigated MLP and RBF to forecast daily solar radiation considering six different combinations of input variables and using data from Dezful, Iran. They concluded that the optimal set of input variables depends on the ANN model being used.

Benghanem and Mellit (2010) evaluated RBF and MLP models as well as regression models to predict daily global solar radiation. They found that the RBF model outperforms the other two types. Rahimikhoob et al. (2013) conducted a comparative study of statistical and ANN models to predict global solar radiation and found ANN to be more accurate. In similar research, Ahmad et al. (2015) considered MLP, nonlinear autoregressive ANN, and an autoregressive (AR) model to forecast solar radiation. They concluded that nonlinear autoregressive ANNs produce the smallest root-mean-square error (RMSE). Reikard (2009) compared the performance of autoregressive integrated moving average (ARIMA), regression, transfer functions, ANN, and hybrid models on six different datasets and at resolutions of 5 to 60 minutes. He concluded that the choice of the best performing model depends on the resolution of interest.

Lauret et al. (2015) used machine-learning techniques along with an AR model to predict solar radiation using historical data from three French islands. They observed that, at a four-hour-ahead horizon, machine-learning models slightly outperform the linear AR model, with the improvement becoming more significant in the case of unstable sky conditions. Koca et al. (2011) evaluated ANN models to predict solar radiation using state and meteorological inputs. They concluded that input variables can significantly affect the performance of ANN models. In similar research, Voyant et al. (2013) used both autoregressive moving average (ARMA) models and MLP to predict solar radiation under multiple forecasting horizons and found that, for a one-hour-ahead horizon, the performances of the models are similar; however, for longer forecasting horizons, MLP outperforms ARMA. It is worth mentioning that using statistical and machine-learning methods to predict solar radiation requires a considerable amount of good-quality historical data. The interested reader can refer to Voyant et al. (2017) for an alternative to these methods when such long historical data are not available.

Several researchers have tried to develop hybrid models by combining the outputs of two or more forecasting methods.

These models are intended to be superior than using each of the embedded methods individually. Some pertinent articles are those by Wang et al. (2015); Monjoly et al. (2017); Ji and Chee (2011), Benmouiza and Cheknane (2013); Voyant et al. (2012); and Voyant, Muselli, et al. (2013).

Datasets and initial analysis

We have identified sources of well-accepted climatic data to evaluate the predictive accuracy of different forecasting models. The most obvious database is the *typical meteorological year* (TMY3 2005) data, which is freely available for thousands of locations worldwide and is the most widely referenced dataset. Note that beam and diffuse irradiation components are estimated from models, but horizontal irradiation, which is what was used in this study, is usually measured at site. TMY3 data for three cities (Phoenix, Arizona; Miami, Florida; and Chicago, Illinois) that have different seasonal and weather behavior have been analyzed in this study. In addition, we have also used historical horizontal irradiation data (measured hourly) as well as cloud cover data provided by a general weather services provider, namely, Weather Underground (WU).

A previous study (Inanlouganji et al. 2017) evaluated seasonal autoregressive integrated moving average (ARIMA) models by training them with measured 2012 data and testing them against measured 2013 data in terms of both measured irradiation and atmospheric clearness index as the random variables. Models using both random variables were rather no better, and in some cases worse, than a simple forecast approach that assumes consecutive days to be identical. This inferior performance was attributed to short-term random seasonal variability in weather at the location, which ARIMA models fail to capture properly. This led to the conclusion that to improve forecasts it is essential to include an independent or regressor variable that captures such short-term weather and location-specific fluctuations of the sky conditions. The cloud cover variable was selected as a logical choice because it is reported in most climatic datasets and is a convenient and intuitive overall variable which captures the "nonclear" condition of the sky. The choice of this variable is consistent with previous studies as well.

Model forms

A simple approach is to use linear models with cloud cover as a regressor variable. Including radiation and/or cloud cover lagged terms is likely to improve forecast accuracy (such models are referred to as lagged moving average models with input variables or LMX models). The model forms investigated are described as follows.

Model forms for one-hour-ahead predictions

The functional form of the LMX model identified for individual months is given as

$$\widehat{I_t} = \sum_{i=1}^{2} \beta_i I_{t-i} + \beta_3 I_{t-24} + \sum_{i=1}^{2} \alpha_i cc_{t-i} + \alpha_3\, cc_{t-24} + \alpha_4 \widehat{cc_t} + \alpha_5 Time \qquad (1)$$

where $\widehat{I_t}$ is the predicted irradiation at time t, I_{t-i} is the measured irradiation at time lag i, $\widehat{cc_t}$ is the predicted cloud cover at time t, cc_t is the measured cloud cover at time t, and the variable *Time* is a categorical variable in the range [1, 24] representing the hour of day index. Hence, this approach consists of 12 different models, which is more accurate than the single annual LMX model.

It is worth mentioning that we have also evaluated models using the same functional form but fitted for the entire year using an additional categorical variable to denote the month of the year. These models were found to be less accurate than fitting individual months, and so their analysis results are not presented here. Further, we also evaluated monthly models using different regressor variables (differences in cloud cover between one-hour lags) and found them to be poorer than Equation 1 (Inanlouganji et al. 2017).

Model forms for 24-hour-ahead predictions

Unlike hourly forecasts at one-hour rolling horizon, models for 24-hour predictions are done once at the end of the previous day and not updated. Hence, the model structure cannot include hourly lags of solar radiation because these values are not known. Also, the model has been simplified by dropping hourly lags of cloud cover from the set of input variables while retaining the cloud cover forecast for the corresponding hour only. Such models are bound to result in a loss in prediction accuracy. The LMX model for 24-hour-ahead forecasting horizon is also identified for individual months of the year and assumes the following form:

$$\widehat{I_t} = \beta_1\, I_{t-24} + \alpha_1\, cc_{t-24} + \alpha_2 \widehat{cc_t} + \alpha_3 Time \qquad (2)$$

We have also found that representing cloud cover term as the average of t and $t-1$ (rather than of t alone) does not improve the forecast accuracy (Inanlouganji et al. 2017), and so the results of such models are not reported in this article.

ANN model

Recall that most of the published papers found ANN to be more accurate than traditional regression models. There are several textbooks which deal with ANNs (for example, Bishop 1994; Haykin 1994; Hagan et al. 1996; Fausett 1994). A commercial software package was used to fit and evaluate the ANN model. The ANN architecture is basically defined by network parameters, namely, the number of hidden layers, the number of hidden units in each layer, the choice of the transfer function, and the gradient descent parameters, such as the learning rate, validation set, and so on. The standard version of back propagation algorithm was employed to train the neural networks, even though other forms can be used (Premalatha and Valan Arasu 2016). Note that the ANN models for one-hour- and 24-hour-ahead forecasting assume the same set of input variables as the corresponding LMX models plus the month index. Hence, only one model is fit over the whole year instead of individual months. Further, one hidden layer composed of 11 nodes was assumed, and the sigmoid transfer function was used for all hidden units.

Baseline model

We need to define a baseline forecast model against which the improvements achieved by the various models can be compared. In this study, we define the baseline model as the *simple forecast approach*, which requires no model, because we assume that hourly irradiation over consecutive days are identical; in other words, the values for the next 24 hours will be identical to those of the previous 24 hours, for which measured values are available. Thus:

$$\widehat{I_t} = I_{t-24} \tag{3}$$

Other baseline models have been proposed in the literature. For example, the persistence model (there are two variants: basic and smart) proposed by Perez et al. (2013) is based on a clear sky index, which is defined as the ratio between measured global horizontal irradiation to that on a clear sky (which, in turn, is determined from a model which requires measured variables such as water vapor, ozone, and so on). This model assumes that the clear sky index for each time horizon depends only on the lagged values of previous sky index values. We chose to use our simpler (and more intuitive) approach as the baseline because it entails neither the use of another model nor of additional measured climatic variables.

Forecast skill parameter

We need a metric that allows us to evaluate the improvement a forecast model provides in terms of the baseline model. Coimbra et al. (2013) propose such a measure, called the *forecast skill parameter, S* (%), which can be defined for any appropriate error metric. Mean absolute error (MAE) is said to be appropriate for linear models; RMSE is more sensitive to large forecast errors and is more appropriate for applications where small errors are tolerable and large errors have high penalties (Lauret et al. 2015). We selected RMSE as the metric of choice. We define Equation 4 as follows:

$$S(\%) = (1 - \ RMSE_{method}/RMSE_{baseline}) \times 100\% \tag{4}$$

Hence, $S = 0\%$ would imply that the method is no better than the baseline model. Positive values of S would mean that the method is an improvement over the baseline model, the limit being $S = 100\%$ for perfect forecasting, in other words, RMSE = 0. Conversely, negative values of S would mean that the method is poorer than the baseline model.

Conditional analyses results

Choosing the response variable

In this section, we address the "conditional" forecast problem—in other words, the model is trained assuming that values of cloud cover are explicitly known. Traditional radiation statistical analyses (e.g., see Duffie and Beckman 2006) tend to favor the use of the atmospheric clearness index (k) as the random dependent variable rather than solar irradiation (I) because much of the sun–earth deterministic geometric variability is filtered out. It would be logical to inquire which of these two variables is likely to result in more accurate forecasts assuming the LMX model (Equation 1). Toward that end, we have evaluated the results of training individual, monthly, one-hour-ahead models with TMY3 data for various locations using both variables during the sunshine hours (with nighttime values and early-morning and late-afternoon hours excluded). The annual average error metrics (MAE, MAPE, and RMSE) estimated using 10-fold cross-validation (see Montgomery et al. 2009 for a description of the metrics and procedure) are summarized in Table 1. Note that for consistency in comparing the accuracy of both modeling approaches, the model predictions of k had to be converted into I values. It is clear from Table 1 that for all three locations, MAE, MAPE, and RMSE, the model with I as the random variable outperforms the one using k. Hence, the variable I has been selected as the dependent variable in all subsequent analyses.

One-hour-ahead forecasting

The LMX model (Equation 1) and the ANN model have been evaluated against the simple forecast baseline model (Equation 3) using TMY3 data for the same three cities, and a 10-fold cross-validation approach was used to obtain

Table 1. Error metrics of hourly I forecasts for 1-hr ahead LMX models using different response variables (I and k).

	I				k			
Location	MAE	MAPE	RMSE	CVRMSE	MAE	MAPE	RMSE	CVRMSE
Phoenix	25	0.12	45	0.21	70	0.35	131	0.66
Chicago	35	0.23	54	0.36	75	0.52	139	0.97
Miami	44	0.23	69	0.36	72	0.37	137	0.71

Note: MAE and RMSE are in units of W/m^2.

Table 2. Validation error metrics and forecasting skill parameter (S) for 1-hr forecast for LMX2 models.

	Simple Forecast			LMX				ANN			
City	RMSE	CVRMSE	MAPE	RMSE	CVRMSE	MAPE	S	RMSE	CVRMSE	MAPE	S
Phoenix	93	0.34	0.17	51	0.19	0.11	45.20%	47	0.15	0.1	49.50%
Chicago	111	0.56	0.27	51	0.25	0.14	54.10%	57	0.23	0.13	48.70%
Miami	118	0.46	0.22	70	0.27	0.16	40.70%	64	0.23	0.15	45.80%

Note: RMSE is in units of W/m^2.

reliable estimates of the error metrics for each individual month. These metrics are averaged over the year and assembled in Table 2, along with the forecast skill parameter S (Equation 4). We note that:

1. The proposed monthly LMX model greatly outperforms the simple forecast method; S values range from 40% to 54%. This considerable improvement in forecast accuracy is due to the inclusion of cloud cover and radiation lags as regressor variables.
2. The RMSE values reduce from 90 W/m^2 to 120 W/m^2 for the simple forecast method to 50 W/m^2 to 70 W/m^2 for the other two models (average decrease close to 50 W/m^2). The large model residuals resulting from the simple forecast method are greatly reduced when LMX or ANN models are used.
3. Neural network models outperform the proposed LMX model for Phoenix and Miami but not for Chicago. This indicates that, for Chicago, fitting monthly regression models instead of just one annual ANN model is preferable, in other words, more effective in avoiding large prediction errors.
4. The prediction accuracy of the LMX and ANN models depends on the variability specific to the city. For example, both the LMX and ANN models for Phoenix have the lowest RMSE values probably because of relatively low irradiation variability in the sunny location. Again, both models have the largest RMSE values for Miami.

24-hour-ahead forecasting

We have also evaluated the performance of different forecasting models for 24-hour-ahead predictions using TMY3 data. The associated error metrics determined from a 10-fold cross-validation are assembled in Table 3, from which the following conclusions can be drawn:

1. For all three cities, both ANN and LMX 24-hour models outperform the simple forecast model; the values of the parameter S are in the range of 17% to 31%. The RMSE values are now in the range of 70 W/m^2 to 90 W/m^2, while those of the simple forecast model are in the range of 90 W/m^2 to 120 W/m^2.
2. The 24-hour forecast models are poorer in terms of RMSE and S values than the one-hour rolling horizon models; this is expected because hourly lag terms were excluded from the model.
3. The ANN model is poorer in terms of the RMSE statistic for Phoenix and Chicago. This could be because only a single annual ANN model is identified, while the LMX2 approach involves identifying monthly models, which are better able to capture the seasonal changes in the solar radiation trend and tend to avoid large forecasting errors. Given that ANN models are more difficult to train and deploy than LMX models, we contend that the LMX model should be seriously considered for field deployment despite several studies finding ANN models to be superior in forecast accuracy.

Figures 1 and 2 clearly allow visualizing the variations in the coefficient of variation of the root-mean-square error (CVRMSE) values for different months for Phoenix and Chicago of the three types of models evaluated. Results in Miami fall in between these two cities and are not shown. From these figures, the following important observations can be made:

1. For any given city, the CVRMSE is highest for the simple forecast method, and this error measure decreases as one switches to 24-hour-ahead LMX model. Further improvement could be achieved by using the one-hour

Table 3. Error metrics and forecasting skill parameter (S) for 24-hr forecast hourly models.

	Simple Forecast			LMX				ANN			
City	RMSE	CVRMSE	MAPE	RMSE	CVRMSE	MAPE	S	RMSE	CVRMSE	MAPE	S
Phoenix	93	0.34	0.17	69	0.29	0.14	25.80%	73	0.23	0.12	21.50%
Chicago	111	0.56	0.27	76	0.47	0.21	31.50%	92	0.39	0.18	17.10%
Miami	118	0.46	0.22	86	0.43	0.19	27.10%	84	0.31	0.16	28.80%

Note: RMSE is in units of W/m^2.

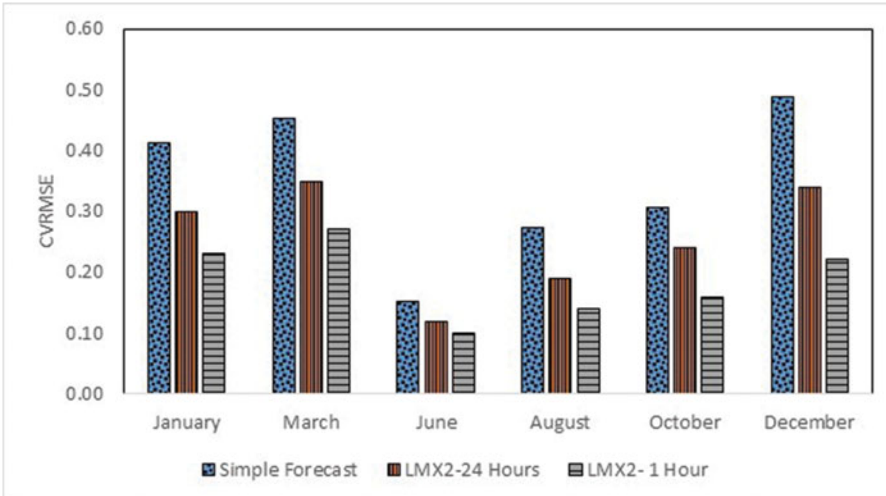


Fig. 1. CVRMSE values for three different models: Phoenix (TMY3 data).

rolling horizon LMX model. These findings are consistent with our intuition.

2. The magnitude of the previously mentioned improvements differs by month for a given city. More interestingly, the variations in CVRMSE values across different months are not the same for all cities. For example, while the variation is quite significant for Phoenix, this is not the case for Chicago. This trend is reflective of the monthly weather patterns in these cities.

Four-hour-ahead rolling horizon forecasting

For forecast horizons smaller than 24 hours, we need to develop a procedure involving a combination of one-hour- and 24-hour-ahead LMX models. One such algorithm is proposed for predicting solar radiation at four-hour-ahead rolling horizon under the presumption that the hourly forecast of the cloud cover variable over all the hours of the following day are provided by the weather service at the beginning of each day. Note that, in all the following steps, when the measured solar radiation values are not available, the algorithm assumes that the last prediction made for that time period is the "measured" value.

Step 0. At the beginning of the day (when the forecasting process is to be initiated), use the 24-hour-ahead LMX model (Equation 2) to generate initial hourly predictions for the first two hours of the day.

Step 1. At the start of the first hour of the operating period, use the one-hour-ahead LMX model (Equation 1) to generate initial predictions for the third and fourth hours of the day.

Step 2. At the start of the second hour of the day, update the initial predictions made for the third and fourth hours of the day, and generate initial predictions for the fifth hour using Equation 1.

Step 3. At the start of the third hour of the day, update the predictions made for the third, fourth, and fifth time periods, and generate the initial prediction for the sixth hour of the day using Equation 1.

Step 4. Starting from the fourth hour of the day and for all subsequent hours, make the initial predictions or update

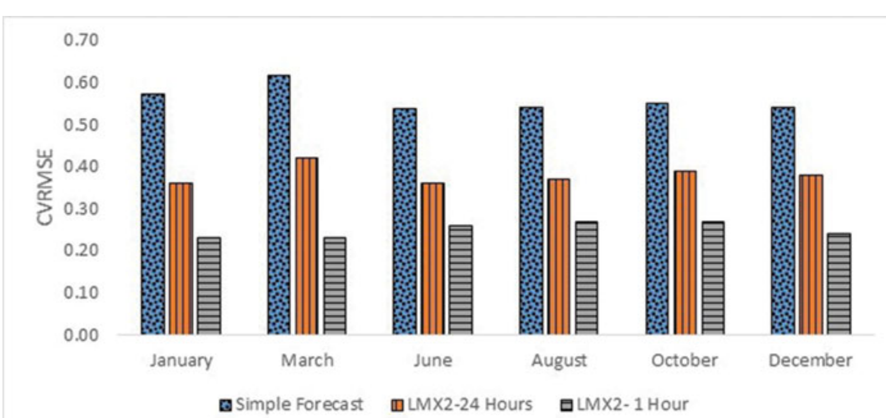


Fig. 2. CVRMSE values for three different models: Chicago (TMY3 data).

Table 4. Values of forecast skill parameter S (%) compared to simple forecast model for different forecast periods and locations.

	24 hour			One hour	
Horizon location	LMX (%)	ANN (%)	Four hour LMX (%)	LMX (%)	ANN (%)
Phoenix	25.80	21.50	39.78	45.20	49.50
Chicago	31.50	17.10	41.96	54.10	48.70
Miami	27.10	28.80	34.51	40.70	45.80

the predictions made for $t+1, \ldots, t+k-1$ hours of the day, where k is the number of forecasts that need to be generated at hour t of the day, using Equation 1.

The performance of the proposed algorithm at the four-hour rolling horizon in terms of the forecast skill parameter S are assembled in Table 4 for all three cities using TMY3 data. To allow better comparison, the values of S for the 24-hour- and one-hour-ahead rolling horizons using both LMX and ANN models are also included. It must be pointed out that, at each forecasting period, four hourly values of I are forecast. The model error at each time step is then calculated as the mean residual value over these four values. Repeating this process over all the prediction periods yields the annual mean values of RMSE, from which the skill parameter can be determined.

From Table 4, we observe that the proposed four-hour rolling algorithm is more accurate than the simple forecast method (range of S values for LMX models in the range of 35% to 42%). More important, the proposed four-hour LMX algorithm is more accurate than simply using the 24-hour model, but not as good as the one-hour model forecast; both of these trends are to be expected. The improvement of the four-hour algorithm compared to the 24-hour-model forecast is about 30% to 50% in relative terms. We notice, also, that the difference in error metrics of the four-hour algorithm is not the same for all three cities. For example, the improvement is S is about 40% for Chicago and Phoenix, while it is about 35% for Miami.

Unconditional analysis using forecast cloud cover analysis

Creating groups of cloud cover data from WU data

The analysis has so far assumed that hourly values of measured cloud cover were known at least one day in advance, and the resulting evaluations of the various models were contingent on this assumption. However, during practical deployment, cloud cover values also need to be forecast, and this task is done by various weather agencies using proprietary algorithms. One such agency, Weather Underground, has been selected for this study. WU provides such forecasts free of charge for several locations. The final aspect of this research would involve investigating the magnitude of forecasting error when the cloud cover forecast is itself subject to error. We must point out that this analysis was done with data gathered from WU after this project was initiated; thus, we had a dataset spanning only about six months (August 2016 to February 2017) for the three locations.

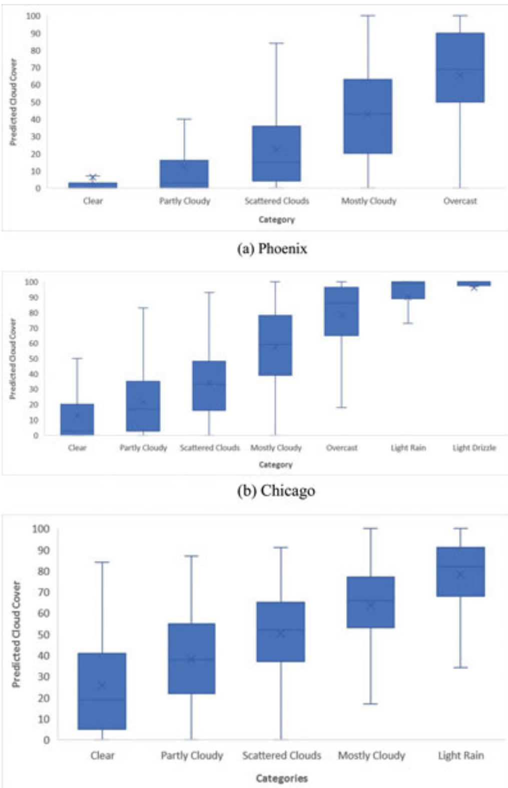
The WU site makes live (i.e., once every day) predictions of cloud cover for each hour of the following day, which are reported as numbers between 0 and 100. The live data feed of actual cloud cover as measured on site does not provide numerical values but simply reports sky conditions in terms of descriptive expressions such as *clear, partly cloudy, scattered clouds, mostly cloudy*, and *overcast*. Given this disconnect between numerical and categorical values, we first need to assign a numerical value to each category of individual hourly cloud cover. The number of categories reported by WU was close to 10 groups. However, a preliminary analysis revealed that some categories contain very few observations, and some of the categories have very similar mean values.

A clustering analysis identified discrete groups followed by multiple statistical t tests to evaluate variability between the category means. For each city, the student t test is used to compare the means for each set of adjacent groups. If the differences in means are statistically significant, we can conclude that the forecast value assigned is a reliable surrogate for the measured value. The results of the t tests for Phoenix are summarized in Table 5. Note that the p values are equal to zero up to three decimal points, indicating that the differences in means are significant for all three cities and all identified categories. The box plots for each category and for each of the three cities are assembled in Figures 3a, 3b, and 3c to illustrate the magnitude of the mean values of the various groups as well as the intra- and intergroup data scatter.

From these figures, we can conclude that the number of categories and their corresponding mean values are location dependent due to differences in weather conditions. Further, the magnitude of the variability in the numerical predicted cloud cover values are also location dependent.

Table 5. Student t tests results for means of different cloud cover categories using WU predictions for Phoenix for six months.

City	Measured cloud cover	Mean	Standard deviation	p Value
Phoenix	Clear	6	16	—
	Partly cloudy	12	19	$<< 0.001$
	Scattered clouds	22	22	$<< 0.001$
	Mostly cloudy	43	27	$<< 0.001$
	Overcast	65	28	$<< 0.001$



(a) Phoenix

(b) Chicago

(c) Miami

Fig. 3. Boxplots of cloud cover forecasts for the three cities using WU data.

Forecast model errors using cloud cover forecasts

Finally, we asked the following question: By how much would the model prediction degrade if the LMX models were based on predicted cloud cover instead of measured values? A difficulty was that the cloud cover data provided by WU and analyzed here were not accompanied by the corresponding measured values of hourly solar radiation. Consequently, we had to resort to the use of TMY3 data, which does provide measured cloud cover data as a number in the range [0, 10]. A simple normalization of this TMY3 data involved multiplying the cloud cover values by 10 to convert the variation range to [0, 100] to be consistent with that adopted by WU. These scaled measured hourly cloud cover values are then replaced by the mean value of the corresponding category.

Two separate modeling evaluations were performed:

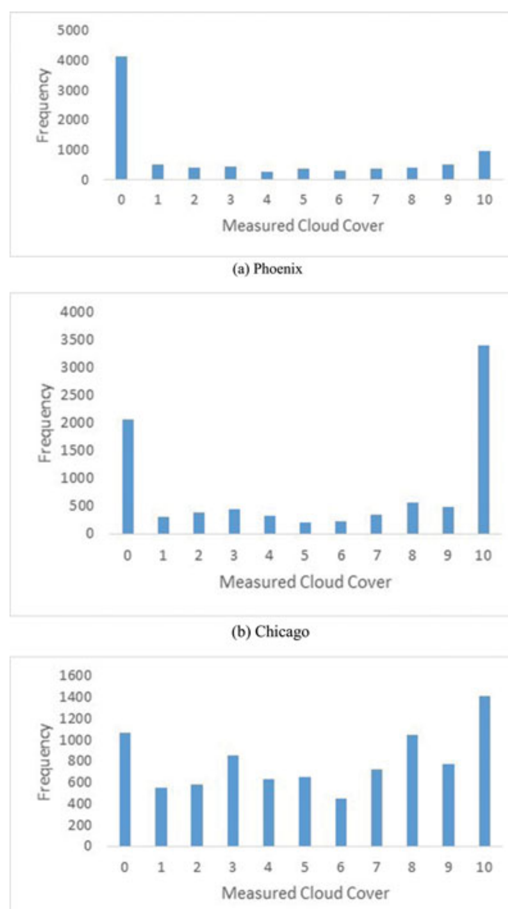
1. *Original data analysis*—More specifically, the hourly daytime values of I and cloud cover from the TMY3 files were used to train and test LMX models using 10-fold cross-validation.
2. *Transformed data analysis*—The numerical values of the individual hourly cloud cover data were modified to the mean values of the group closest to them as identified using WU data. The resulting dataset was used to train and test LMX models using 10-fold cross-validation.

The error metrics—namely, MAE, MAPE, RMSE, and CVRMSE—for each month were averaged over the year and are assembled in Table 6. Because the transformed dataset consists of cloud cover values collapsed into the closest mean value, there is no intravariability in the groups, and one would have expected a loss in model forecast accuracy reflected by higher forecast error metrics. Surprisingly, this is not the case. The error metrics of models identified from both the data are almost identical. We attribute this counterintuitive result

Table 6. Error metrics of LMX models using forecast cloud cover with TMY3 data.

		Error metrics			
City	Data used	MAE	MAPE	RMSE	CVRMSE
Phoenix	Original	37	0.16	62	0.26
	Transformed	37	0.16	62	0.26
Chicago	Original	42	0.26	69	0.42
	Transformed	43	0.26	69	0.42
Miami	Original	53	0.27	84	0.43
	Transformed	53	0.27	84	0.43

Note: MAE and RMSE are in units of W/m^2.



(a) Phoenix

(b) Chicago

(c) Miami

Fig. 4. Frequencies of hourly daytime cloud cover categorical values using TMY3 data. CC = 0 corresponds to very clear sky conditions.

to the fact that the functional form of the forecast model, because it contains lagged values of I and cloud cover, is flexible and robust enough that it can adjust the model coefficients accordingly without any loss in forecast accuracy. Note that in each analysis the same dataset is being used to train and test the models.

A factor that provides some insight into the forecast accuracy of the LMX model is the distribution of measured cloud cover data. For example, for Phoenix, most observations fall into the "very clear sky" category (see Figure 4a), and the distribution for Chicago (Figure 4b) is heavily weighted toward the two extremes. This means that, for most of the observations, the error resulting from replacing the cloud cover values with their closest mean would be small and would result in very little degradation in model accuracy.

Summary and conclusions

This study proposes hourly irradiation forecast models that can be identified by linear regression involving hourly lags in radiation and cloud cover along with hour of the day as input variables. The model structure of the LMX models, which are identified for individual months of the year, should be modified depending on whether the forecasts are to be done on a one-hour rolling horizon (including two lags) or as a single block of 24 hourly forecasts. Lagged values of cloud cover and radiation will be used as input variables to these models, which, to the best of our knowledge, has not been studied previously.

How these two models can be used in conjunction for four-hour rolling horizon forecasting has also been addressed. The algorithm proposed for four-hour-ahead forecasting is new and seems to perform well. The forecast accuracy of these models has been evaluated with yearlong data from three locations with different climatic behavior. The forecast improvement is expressed in terms of a forecast skill parameter (S) compared to a simple baseline forecast method, which simply assumes that radiation at time t is equal to that at time $t - 24$. A value of $S = 0\%$ implies no improvement, while $S = 100\%$ would denote perfect prediction.

The average annual values of S range from 40% to 54% for the three locations for LMX models used to make one-hour-ahead forecasts. Neural network models are slightly superior to LMX models for two of the cities; this was not the case for the third location. At the 24-hour-ahead forecasting horizon, the values of S range from 26% to 32% for the LMX model and outperform the ANN model in terms of RMSE (S values in the range of 17% to 29%). A possible explanation is that training and deployment of 12 different monthly models helps avoid large seasonal-dependent prediction errors, while the ANN model identified on an annual basis does not have the same advantage.

This study showed that the proposed algorithm for four-hour rolling forecast is distinctly superior to the 24-hour-ahead LMX model. The S values of the former compared to the simple forecast method were in the range 35% to 42%, which is superior to that of the 24-hour-ahead LMX model (range of S values 26% to 32%). This justifies the benefit of adopting the proposed forecasting algorithm involving one-hour and 24-hour forecast values rather than simply using the 24-hour forecast model.

Finally, the degradation in prediction accuracy of the LMX model if predicted cloud cover instead of measured values were used is investigated. The analysis led to the rather counterintuitive conclusion that no loss in forecast accuracy would result, which could be attributed to the functional form of the model being sufficiently flexible and robust. This is, of course, contingent on the LMX model being both trained and deployed using forecast cloud cover values as the regressor variables.

The regression model forms and the forecast algorithm proposed in this article should be evaluated for more locations worldwide before they can be used with confidence. Instead of using TMY3 data for a location, the effect of using historical, multiyear, time series data should also be reevaluated (our preliminary analysis found it to be undesirable). Finally, a promising future direction in terms of forecast models could entail evaluating other machine-learning techniques, such as random forests and Gaussian process regression, and comparing their prediction performance to the regression models proposed in this study. However, one could argue that using simple transparent regression models, even if they are slightly less accurate, is more easily accepted by professionals with limited statistical background.

Nomenclature

ANN	artificial neural network
CC	cloud cover
CVRMSE	coefficient of variation of the root-mean-square error
I	horizonal total solar irradiance, W/m^2
LMX	lagged moving average model with input variables
MAE	mean absolute error, W/m^2
MAPE	mean absolute percentage error
RMSE	root-mean-square error, W/m^2
R^2	coefficient of determination
S	forecast skill parameter defined by Equation 4, %
t	time
TMY3	typical meteorological year version 3
WU	Weather Underground organization

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