Deep Long Short-Term Memory with Separation Models for Direct Normal Irradiance Forecasting: Application to Tamanrasset, Algeria

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Hanane Atmani*[1], Hassen Bouzgou[2] and Christian A. Gueymard[3]

[1] Department of Electronics, University of Batna 2, Batna, Algeria
[2] Department of Industrial Engineering, Laboratory of Automation and Manufacturing, University of Batna 2, Batna, Algeria
[3] Solar Consulting Services, Colebrook, NH, USA

*correspondence E-mail: h.atmani@univ-batna2.dz

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EXTENDED ABSTRACT

Solar energy is a vast and clean resource that can be harnessed with great benefit for humankind. It is still currently difficult, however, to convert it into electricity in an efficient and cost-effective way. One of the ways to produce energy is the use of various focusing technologies that concentrate the direct normal irradiance (DNI) to produce power through highly-efficient modules or conventional turbines. Concentrating technologies have great potential over arid areas, such as Northern Africa. A serious issue is that DNI can vary rapidly under broken-cloud conditions, which complicate its forecasts [1]. In comparison, the global horizontal irradiance (GHI) is much less sensitive to cloudiness. As an alternative to the direct DNI forecasting avenue, a possibility exists to derive the future DNI indirectly by forecasting GHI first, and then use a conventional separation model to derive DNI.

In this context, the present study compares four of the most well-known separation models of the literature and evaluates their performance at Tamanrasset, Algeria, when used in combination with a new deep learning machine methodology introduced here to forecast GHI time series for short-term (15-min) horizons. The proposed forecast system is composed of two separate blocs. The first bloc seeks to forecast the future value of GHI based on historical time series using the Long Short-Term Memory (LSTM) technique with two different search algorithms. In the second bloc, an appropriate separation (also referred to as "diffuse fraction" or "splitting") model is implemented to extract the direct component of GHI.

LSTMs constitute a category of recurrent neural network (RNN) structure that exhibits an excellent learning and predicting ability for data with time-series sequences [2]. The present study uses and evaluates the performance of two novel and competitive strategies, which both aim at providing accurate short-term GHI forecasts: Unidirectional LSTM (UniLSTM) and Bidirectional LSTM (BiLSTM). In the former case, the signal propagates backward or forward in time, whereas in the latter case the learning algorithm is fed with the GHI data once from beginning to the end and once from end to beginning. One goal of this study is to evaluate the overall advantages and performance of each strategy.

Hence, this study aims to validate this new approach of obtaining 15-min DNI forecasts indirectly, using the most appropriate separation model. An important step here is to determine which model is suitable for the arid climate of Tamanrasset, a high-elevation site in southern Algeria where dust storms are frequent. Accordingly, four representative models have been selected here, based on their validation results [3] and popularity: 1) Erbs model [4]; 2) Maxwell's DISC model [5]; 3) Perez's DIRINT model [6]; and 4) Engerer2 model [7].

In this contribution, 1-min direct, diffuse and global solar irradiance measurements from the BSRN station of Tamanrasset are first quality-controlled with usual procedures [3, 8] and combined into 15-min sequences over the period 2013–2017. The four separation models are operated with the 15-min GHI forecasts obtained with each LSTM model, then compared to the 15-min measured DNI sequences. Table 1 shows the results obtained by the two forecasting strategies for the experimental dataset.

Error statistic	LSTM	BiLSTM
RMSD (%)	20.39	**7.34**
MAE (%)	76.79	**5.09**
MBD (%)	**-0.90**	1.06
R^2 (%)	0.87	**0.98**

Table 1. Statistical results of estimated GHI from GHI measured at Tamanrasset with a 15-min time step, using two strategies of LSTM. The best results appear in boldface.

To evaluate the performance of the combination of LSTM GHI forecasts with each separation model, four metrics are used: Root Mean Square Difference (RMSD), Mean Bias Difference (MBD), Mean Absolute Error (MAE), and t-Statistic (t-Stat). The specific results obtained with BiLSTM are summarized in Table 2.

Error statistic	DISC	DIRINT	Engerer2	Erbs
RMSD (%)	63.7	62.9	**53.3**	94.2
MAE (%)	46.3	46.0	**34.0**	60.6
MBD (%)	9.5	11.7	**0.3**	43.6
t-Stat (%)	16.3	20.4	**0.7**	56.4

Table 2. Statistical results of estimated DNI from BiLSTM GHI forecasts at Tamanrasset with a 15-min time step, using four different separation models of the literature. The best results appear in boldface. Percent results refer to the mean measured DNI of 426.0 W/m^2.

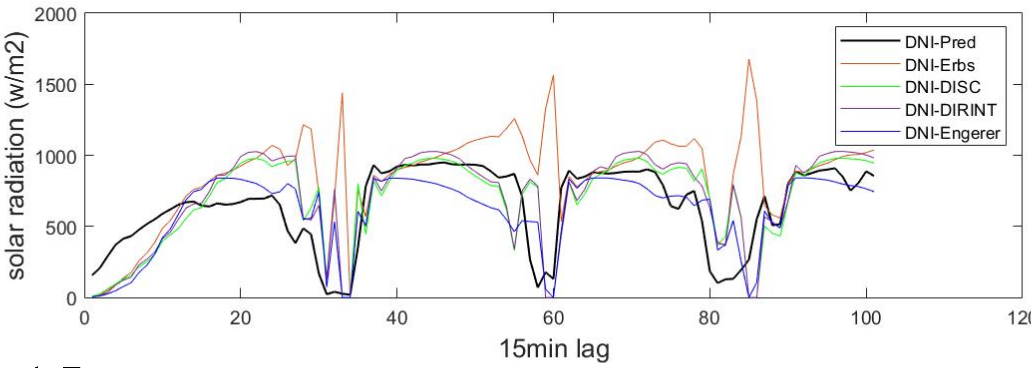

Figure 1. Time series of the observed (dark solid line) and estimated DNI (color lines) by the Erbs, DISC, DIRINT, and Engerer2 separation models at Tamanrasset during a 4-day exemplary period, using 15-min GHI forecasts as input and excluding nighttime periods.

From Table 2, the results for the DISC and DIRINT models appear similar and much better than Erbs, which is affected by irregular and unphysical spikes (Fig. 1). It is clear that, based on all statistical indicators, the best performing model is Engerer2, thus confirming previous results [3]. Interestingly, the reduction of bias achieved by Engerer2 is substantial in comparison with all other separation models.

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