Deep Learning for Solar Irradiance Forecasting

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The development of efficient renewable energy systems is of significant importance in the context of mitigating global warming effects. Our paper addresses the short-term prediction of solar irradiance based on specialized meteorological measurements which represents a subtask from EGC Challenge 2018. The goal is to forecast solar irradiance over Réunion Island using data collected between 2014 and 2015, at fifteen stations, equipped with precision solar radiation measurement instruments and additional meteorological sensors. Such a prediction task can be approached via classical time series analysis models which are based on short-term dependencies such as auto-regressive predictors: AR, ARX, ARMAX. Following this approach, Di Piazza et al. (2016) performs an hourly solar irradiation forecast from 8 up to 24 hours in the future. In contrast, Yadav et al. (2013) compares two network architectures, Recurrent Neural Networks (RNN) and Multilayer Perceptron (MLP), on the task of predicting daily, monthly and hourly irradiance values. Qing and Niu (2018) concluded that LSTM is more accurate than a multilayer feed-forward neural network. Herein, we focus on deep learning prediction methods, in particular RNN (LeCun et al., 2015) with memory cells such as Long Short-term Memory (LSTM) and Gated Recurrent Units (GRU).

Solar irradiance prediction. The dataset is composed of diffused global irradiance (FG), direct irradiance (FD) and meteorological data: atmospheric air pressure, relative humidity, external temperature and wind speed and direction. Formally, we can describe this task as follows: given previous sensor readouts $\mathbf{y}^t, \mathbf{y}^{t-1} \ldots \mathbf{y}^{t-m+1}$ where $\mathbf{y}^{t-m+1}$ indicates all measurements at m time steps in the past from the current time t, we predict the irradiance value x^{t+k} with k being the future time step of interest. The daily solar irradiance, denoted as $k_b = \frac{\mathrm{FD}}{\mathrm{FG}}$, is defined as the ratio between the direct solar irradiance and the global solar irradiance. We pre-process the dataset to remove entire days when dealing with too many missing data. Next, we compute the predicted variable k_b and normalize the dataset to $[0, 1]$ range. Our objective is to predict the solar irradiance one hour in the future, $k = 60$.

Architecture. The input layer consists of LSTM and GRU cells which take in the past m measurements. We experimented with different numbers of time steps $m \in \{5, 10, 15, 30\}$ as well as different sizes for the layer. The final reported result uses a layer of size 150 and the input data that merges $m = 30$ previous time steps. Regardless of the type of cells used in the input layer the hidden layer is an LSTM layer of size 70 with *tanh* activation. The final layer is a fully connected layer also with *tanh* activation. For the first architecture we consider a single valued expected output with the goal of predicting x^{t+k} where k represents the future time step of interest and t is the current time step. The second model uses multiple valued

	Moufia		Possession		Saint André		Saint Leu		Saint Pierre	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
LSTM seq.	**0.070**	**0.046**	**0.122**	**0.067**	0.058	0.039	0.161	0.092	**0.175**	**0.100**
GRU seq.	0.073	0.050	0.129	0.068	**0.056**	**0.031**	**0.154**	**0.087**	0.190	0.114
LSTM	0.083	0.062	0.128	0.070	0.060	0.035	0.158	0.095	0.178	0.101
GRU	0.080	0.056	0.137	0.074	0.061	0.034	0.161	0.096	0.185	0.110
Arima XGB	0.249	0.193	0.245	0.195	0.257	0.208	0.255	0.203	0.241	0.183
Arima MLP	0.283	0.202	0.283	0.214	0.332	0.255	0.315	0.243	0.286	0.205

TAB. 1 – *Results obtained on the evaluation sets for sequential and single valued network outputs. The last lines present the baseline results obtained by Bruneau et al. (2018).*

output, namely, the sequence of next k values, $x^{t+1} \ldots x^{t+k}$. This method enforces a more consistent prediction between all the time step values. We consider all predictions to be of equal importance such that the evaluation function uses a weight of $\frac{1}{k}$ for each of the predicted values. This method can also use different weights to increase importance for a given step. We train the models using Adam (Kingma and Ba, 2014) with the recommended hyper-parameter values. Also, we use dropout with probability $p = 0.2$ to regularize and reduce overfitting.

Results and conclusions. The dataset is split between training and evaluation, year 2014 is used for training and 2015 for testing and validation. Training is done using *tensorflow* as a backend and *keras* as frontend, with a batch size of 64 for 20 epochs. We use as a cost function the mean absolute error (MAE). For the evaluation step, besides MAE, we also check root mean squared error (RMSE). We present in Table 1 the RMSE and MAE values obtained by the above architectures for each site in particular, as well as the results obtained by Bruneau et al. (2018). In general, LSTM cells perform slightly better than the GRU ones and sequence predictions outperform the single valued output models. When compared with Bruneau et al. (2018), we observed consistently better RMSE/MAE for our models. We achieved the best results on the *Saint André* site, which are roughly four times lower than the baseline. Whilst, the worst performance is obtained at *Saint Pierre*, around 30% lower than the baseline.

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