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Hourly Wind Speed Forecasting Using FFT-Encoder-Decoder-LSTM in South West of Algeria (Adrar)

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Abstract. The fluctuated nature of wind makes it a very challenging phenomenon to track where making an accurate forecast of one of its parameters requires a robust and reliable model. In this study we will focus on the wind speed forecast for wind energy generation purpose which is a very delicate process that requires an accurate prediction results. The wind speed prediction is considered as one of the highest complexity time series problems where the studies proved the efficiency of Recurrent Neural Network (RNN) models and specifically the Long Short Term Memory (LSTM) model that provides accurate prediction with the capacity to handle long-term dependencies. In this paper an hourly wind speed forecasting model was proposed based on Fast Fourier Transform Filter and Encoder-Decoder-LSTM model (FFT-Encoder-Decoder-LSTM), the FFT Filter was used for Data Denoising pro-cess then Max-Min normalization technique was applied to standardize the data and finally the Encoder-Decoder-LSTM model was used for the wind speed prediction. The traditional MPL, Single-layer-LSTM, Encoder-Decoder-LSTM, FFT-MLP and FFT-Single Layer LSTM model were used as benchmark models. While accentuating the effectiveness of data prepro-cessing step in the forecasting process, the efficiency of the models is evalu-ated for 1-hour and 3-hours ahead wind speed forecasting where the FFT-Encoder-Decoder-LSTM showed the best and the more consistent results.

Keywords: Encoder-Decoder-LSTM · Fast Fourier Transform · Wind Speed · Short-Term Forecasting

1 Introduction

One of the most important things that surround and affect basically everything in our daily life is the weather. Many studies had been made in this subject to find a way to put the power of nature in our favor or at least preventing it from leading to disasters. This is what led us to the science we know today as weather forecast-ing. One of the most complicated weather forecasting events is the wind with its two key factors: speed and direction being the most challenging parameters to pre-dict.

As we can see the latest researches in this field focused on the prediction of wind speed for wind power generation purpose[1], considering the need that the world showed these last years of a clean and renewable energy source with a moderate cost and a wide availability [2].A variety of traditional techniques were used for this purpose but deep learning methods provided more accurate predictions with higher performance thanks to its capacity of learning chaotic data and its general-ization ability [3].

The wind speed forecasting is a time series problem which requires a powerful model capable of automatically learning features from a sequence within the temporal ordering and the best fit for this is the Long Short-Term Memory Networks [4]. In this study we proposed a new approach being the FFT-Encoder-Decoder-LSTM for a univariate 1-hour and 3-hours ahead wind speed forecasting using data of Adrar city while highlighting the importance of data preprocessing step in the prediction process. The rest of the paper is structured as follows: sec-tion 2 describes the related works. Section 3 presents the architecture of the pro-posed model. Section 4 explains the data pre-processing steps. Section 5 discuss-es the obtained results and the final section summarizes the study and proposes future works.

2 Literature review

In the last decade, variety of remarkable efforts to solve wind speed forecasting problem using deep learning techniques have been reported. We can see that in 2018 Hui Liu et al, proposed a Variational Mode Decomposition (VMD) - Singu-lar Spectrum Analysis (SSA) - Long Short Term Memory (LSTM) - Extreme Learning Machine (ELM) model for wind speed forecasting. The first step con-sists of decomposing the wind speed data into a series of sub-layers using the VMD algorithm, followed by the extraction of the trend information of all the sub-layers using the SSA method. Finally the forecasting step in which the low-frequency sub-layers resulted from VMD-SSA are fed to a single Layer LSTM while the high-frequency ones to the ELM [5]. In the same year, Yusuf Elmir pro-posed an Artificial Neural Network (ANN), combined with the Genetic Algorithm (GA) for the weights generation in order to predict air temperature, relative hu-midity, atmospheric pressure, mean wind speed of Bchar city the GA-ANN model showed such a good improvements compared to the ANN model alone. The mean error was reduced for each predicted variable from 3.8632 for air temperature, 3.0006% for humidity, 11.0101(mmHg) atmospheric pressure, 2.4065(m/s) for the wind speed to 2.7918, 3.0454%, 10.3271(mmHg), and 2.3599 (m/s) respectively for the GA-ANN [6]. One year later, Yao Liu et al, provided a multistep prediction Discrete Wavelet Transform (DWT)-LSTM mod-el for wind power generation, where the DWT was used in the data preprocessing stage to decompose the time series data into an approximate signal and detailed signals, then z-score normalization method was applied to standardize the de-composed data. Every sub-signal resulted from the previous decomposition was assigned to a separate LSTM for training, and in the final step sub-signals were denormalized and summed to get highly accurate wind power prediction results [7].Two years later, Shobana Devi et al, implemented a robust day-ahead wind power forecasting hybrid model based on Ensemble Empirical Mode Decomposi-tion (EEMD), Cuckoo Search Optimization (CSO), LSTM and Enhanced Forget-Gate network (EFG). The EEMD was used for the decomposition of the wind time series data to get divers subseries where the high frequency subseries are ignored later and the remaining ones are reconstructed to get stationary time series data ,then weight measurements for the intensified LSTM-EFG model were boosted using hyper parameters CS optimization algorithm[8]. In the same year Sambeet Mishraa et al, made a performance comparison of five deep learning models: Deep Feed Forward (DFF), Deep Convolutional Network (DCN), Recurrent Neu-ral Network (RNN), Attention mechanism and LSTM for wind speed and tem-perature forecasting using Multi-Input-Multi-Output (MIMO) modeling structure. Each model was combined with two types of data pre-processing techniques: Discrete Wavelet (DW), Fast Fourier Transformation (FFT) and the results proved the efficiency of the data smoothing aspect [9]. By the end of the year ZHOU et all, reviewed the fundamental wind speed forecasting frameworks with a detailed comparison of the deep learning-related techniques while investigating the advantages and disadvantages of each discussed method. [10].

3 Recurrent Neural Networks (RNN)

Recurrent neural networks, are a category of DNN that make use of previous out-puts as inputs while having hidden states, being the only neural network provid-ing a memory from internal storage which is designed to memorize sequences of data and enable the model to recall it [11] and recognize patterns such as numeri-cal times series data [12].The Back propagation Through Time (BPTT) algorithm is used for the RNN training in order to calculate the gradients and propagation of error and multiply it with weights in all training steps. The main weakness of the traditional RNN model when handling long term dependencies is the gradient vanishing and exploding issues [11]. So a new model has been proposed to over-come RNNs failures which is the long short term memory (LSTM) model.

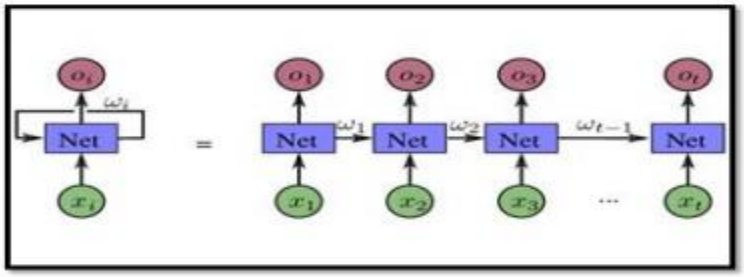

Fig. 1. Recurrent Neural Network Structure.

4 Long short term memory (LSTM)

Long short term memory network is a specific architecture of recurrent neural network which has a long-range dependency that makes it a more powerful time series forecasting tool. An LSTM layer is composed of a sequence of recurrently connected blocks, called the memory blocks, containing one or more recurrently connected memory cells being the computational unit of the LSTM with three multiplicative gates referring to the write, read and reset operations for the cells[12].

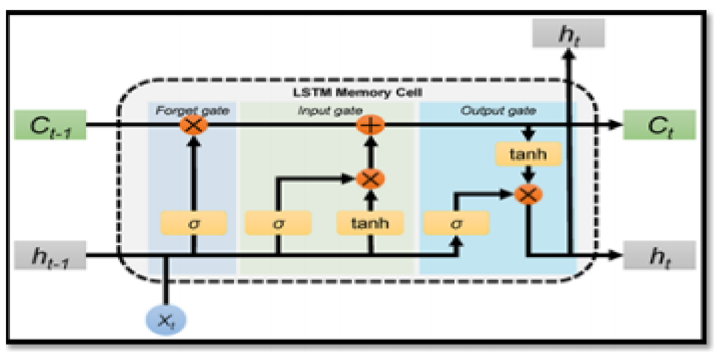

Fig. 2. Long short term memory model Structure.

5 Architecture of the Proposed Model

The entire process of the FFT-Encoder-Decoder-LSTM model is shown in Figure 3. The architecture of the Encoder-Decoder-LSTM model can be represented as follows:

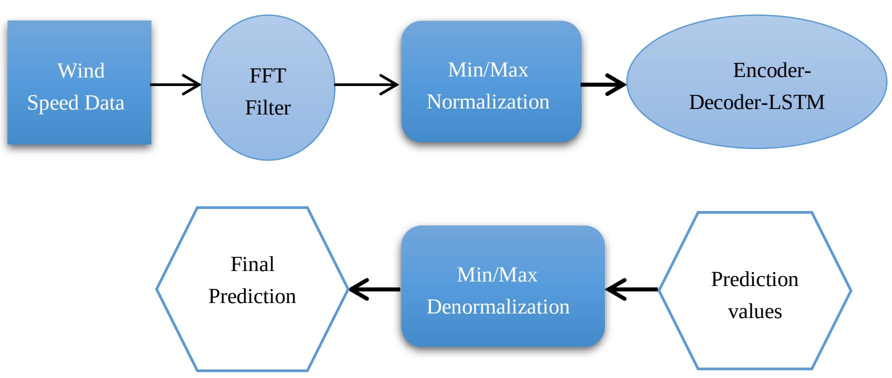

Fig. 3. The process of the FFT-Encoder-Decoder-LSTM model.

5.1 Encoder Decoder Long Short Term Memory (Encoder-Decoder-LSTM)

The Encoder-Decoder-LSTM model used for this experiment and presented in Fig2, is composed of two sub models, an encoder for the encoding and reading part of the input sequence and a decoder for the prediction of each of the encoded input sequences element for a single-step.

- The LSTM model is applied in the encoder and decoder process in order to grant it the full knowledge of what was predicted for the past 1 and 3 hours in the sequence and build an internal state while processing the sequences.

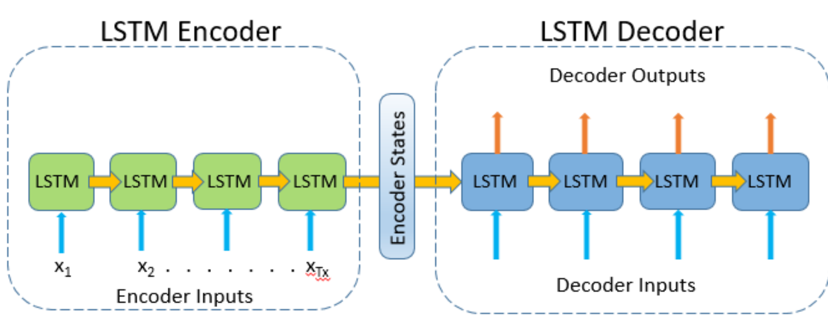

Fig. 4. Encoder-Decoder-LSTM Model Structure.

- In this architecture 1 and 3 hours of mean wind speed data was provided as inputs to the encoder (single hidden layer LSTM) in order to encode the

inputs as elements vector that capture features from the input sequence. At the start, the inner representation of the mean wind speed input sequence is repeated multiple times, once for each time step in the output sequence.
- Then the decoder (single hidden layer LSTM) will output the complete sequence where each of the input units will output a value for 1 and 3 hours wind speed.
- A fully connected layer is provided to interpret each time step in the output sequence. The output layer will finally predict a single step in the output se-quence.
- A Time Distributed wrapper will be added in order to allow the same process to be repeated for each time step in the output sequence while reusing the same weights to make the interpretation.

The Adam Optimization Algorithm The optimizer algorithm used for the Single-Layer-LSTM and the Encoder-Decoder-LSTM is the Adaptive Moment Estimation (Adam) optimizer algorithm. It is an adaptive learning rate optimization algorithm that can be used instead of the classical stochastic gradient descent procedure to update network weights iteratively based on training data [13]. It uses the squared gradients to enhance the training and it takes benefits of momentum by using MA of the gradient in place of gradient itself like SGD with momentum [14].

The RELU activation Function For this experiments we used rectified linear activation function in each model which is a piecewise linear function that checks the sign of the inputs and based on it, it outputs the positive ones and sets the rest as zeros before outputting them , it makes the model easier to be trained and reaches better perfor-mance[15].

$$f(x) = max(0, x) \tag{1}$$

5.2 Dataset and Data Preprocessing

Dataset for this research was obtained from Raspisaniye Pogodi Ltd, Weather for 243 countries of the world site in St. Petersburg, Russia, since 2004. The company has the license for activity in hydrometeorology and other close areas [16]. Five years of wind speed dataset of Adrar city have been used for these experi-mentations from the period between 01 January 2014 to 01 January 2019. 67% of data were used for training from the year 2014 to 2017 and 33% years were used for test from 2017 to 2019, knowing that the data was collected every hour. The main data preprocessing techniques applied to the time series data are: Smoothing data using FFT Filter and rescaling using min-max normalization (1).

Fast Fourier Transform In this paper we make use of the Lowpass FFT filter that performs filtering by using Fourier Transforms which decomposes the time series data into a frequency domain smoother and easier to process by the Encoder Decoder LSTM model and reduces the number of computations needed for the prediction from $O(N\hat{2})$ to $O(NlogN)$ where N is the wind speed time series size [9].

The general process for Lowpass FFT denoising filter can be summarized as fol-lows:

1. The computation of Fast Fourier transform from the wind speed input signal.
2. The procession of the transformed data in the frequency domain.
3. The deletion of the high frequency components to achieve a denoising effect.
4. Reconstruction of the original signal with inverse FFT [9].

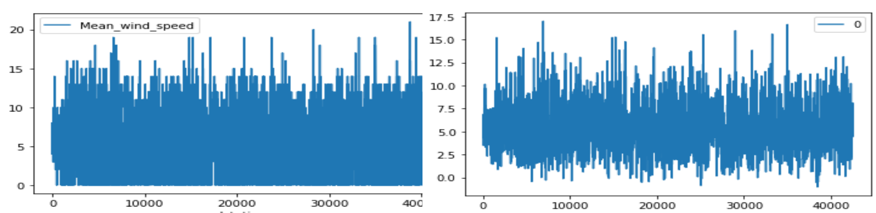

Fig. 5. Wind Speed Data Distribution: (a) before, and (b) after Using Fast Fourier Filter.

Rescaling (min-max normalization) Is a widely used normalization data technique which sets the minimum value of each feature to 0 and the maximum value to 1 and every other value gets trans-formed into a decimal between 0 and 1. [17].

$$Y = (y(t) - min)/(max - min) \tag{2}$$

Where: y (t) is the result of data smoothing using Fast Fourier Transform, and Y is the normalized smoothed data at t.

6 Experiment Results

1-hour ahead wind speed forecasting In these experiments, two classifications with three models have been built: (MLP model, Single-Layer-LSTM model, and the Encoder-Decoder-LSTM mod-el) and the second: (FFT-MLP, FFT-LSTM and the proposed FFT-Encoder-Decoder-LSTM model) The first classification is meant for developing the mod-els without applying the Fast Fourier Transform Filter and the second after apply-ing it. The forecastings RMSE and MAE results are shown in the Table 1. Figures 6 and 7 indicate the outcomes of various models. The table below presents the RMSE and MAE results before and after using the FFT filter for 1 hour ahead wind speed forecast. From Fig6 and Table 1 the RMSE results of the MLP, Single-Layer-LSTM and

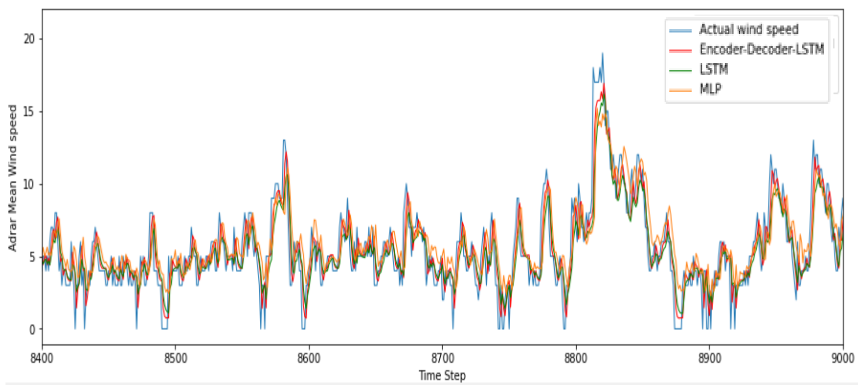

Fig. 6. Comparison of the 3 models for 1-hour ahead forecast.

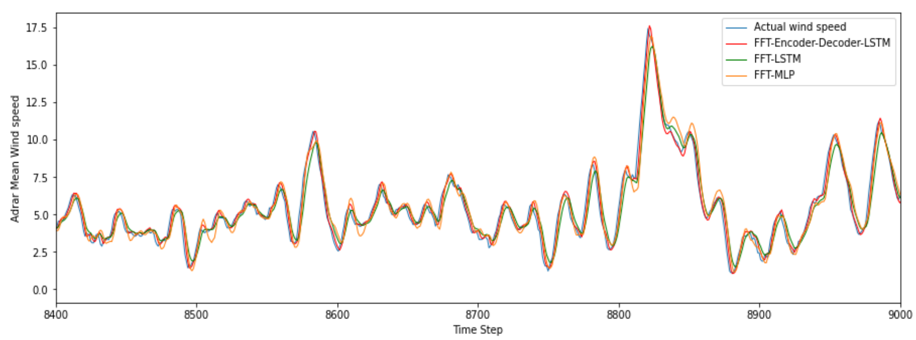

Fig. 7. Comparison of the 3 models for 1-hour ahead forecast after Using FFT filter.

Table 1. RMSE and MAE results for 1-hour Wind Speed Forecast.

Models		**RMSE** (m/s)		**MAE (m/s)**	
MLP	FFT-MLP	1.981	0.194	0.0763	0.009
LSTM	FFT-LSTM	1.631	0.043	0.0612	6.3242e-04
Encoder-Decoder-LSTM	FFT-Encoder-Decoder-LSTM	1.432	0.035	0.0689	6.1734e-04

Encoder-Decoder-LSTM are as follows: 1.981(m/s), 1.631(m/s) and 1.432(m/s) respectively. This indicates that the proposed model gives a better performance in comparison with the other forecasting models.

Remark 1: As we can see in the Table 1, the Single-Layer-LSTM and Encoder-Decoder-LSTM gave close results so we zoomed in the plots in order to better capture the changes.

From Fig 7 and Table 1 The RMSE results of the FFT-MLP, FFT-LSTM and the proposed model are as follows: 0.194(m/s), 0.043(m/s) and 0.035(m/s) respectively.

Remark 2: This confirms the effectiveness of the proposed model and indicates that the use of the FFT filter showed a great improvement in the prediction pro-cess.

6.1 3-hours ahead wind speed forecasting

The same experiments were repeated for a larger time horizon of 3 hours and the forecasting results are shown in Table 2. Figures 8 and 9 indicate the outcomes of various models.

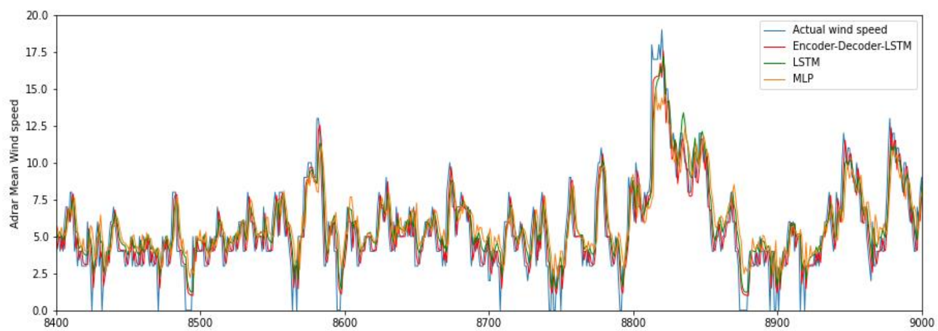

Fig. 8. Comparison of the 3 models for 3-hours ahead forecast.

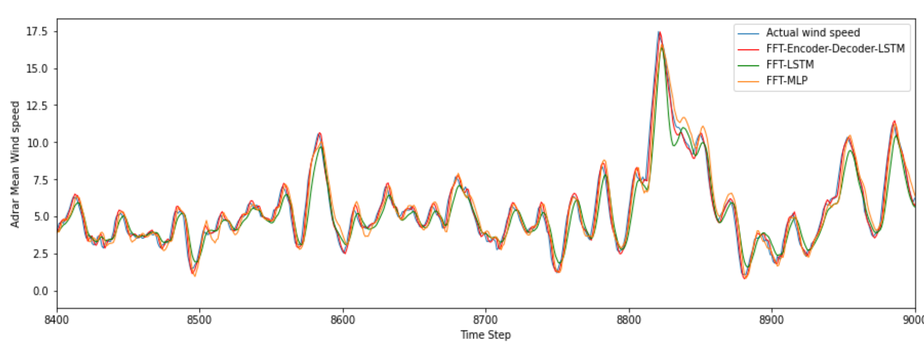

Fig. 9. Comparison of the 3 models for 3-hours ahead forecast.

The table below presents the RMSE and MAE results before and after using the FFT filter for 3 hours ahead wind speed forecast. From Fig8 and Table 2,the

Table 2. RMSE and MAE results for 3-hours Wind Speed Forecast.

Models		**RMSE** (m/s)		**MAE (m/s)**	
MLP	FFT-MLP	2.313	0.869	0.231	0.021
LSTM	FFT-LSTM	2.042	0.592	0.186	0.0086
Encoder-Decoder-LSTM	FFT-Encoder-Decoder-LSTM	1.981	0.487	0.0981	0.0079

RMSE results of the MLP, Single-Layer-LSTM, and Encoder-Decoder-LSTM are as follows: 2.313 (m/s), 2.042 (m/s) and 1.981 (m/s) respectively. This indicates that the Encoder-Decoder-LSTM model accomplishes a better per-formance in comparison with the other forecasting models.

Remark 1: As we can see in the Table 2, the Single-Layer-LSTM and Encoder-Decoder-LSTM gave close results so we zoomed in the plots in order to better capture the changes. -From Fig9 and Table 2,the RMSE results of the FFT-MLP, FFT-Single-Layer-LSTM, and FFT-Encoder-Decoder-LSTM are as follows: 0.869 (m/s), 0.592 (m/s) and 0.487 (m/s) respectively. This indicates that the proposed model achieved a better performance in comparison with the other forecasting models.

Remark 2: Even in a larger time horizon the proposed model still can provide a better performance than the other models.

7 Conclusion

Renewable energy is an active research field that attracted the attention of many new countries. In our study we focused on the wind power generation which is considered as the most promising renewable energy. Specifically we worked on the wind speed forecast which is an important factor involved when choosing a site to host a wind farm and as we know the power generated by the wind is pro-portional to the cube of its velocity. We picked the southwestern parts of the Algerian Sahara (Adrar city) as the area of our study knowing that it contains the only wind farm in Algeria till now with the highest wind speed levels in the whole country.

In this work a short term wind speed forecasting model is developed by combin-ing the Fast Fourier Transform Filter with the Encoder-Decoder-LSTM model for 1 and 3 hours ahead wind speed forecast where the FFT filter was used for data denoising process and the Encoder-Decoder-LSTM for the wind speed predic-tion. A benchmark of models was selected for comparison purpose (MLP, Single Layer LSTM, Encoder-Decoder-LSTM, FFT-MLP and FFT-Single-Layer-LSTM). The experiments were made before and after the application of the FFT Filter to better extract the features of each model.

The results showed that the proposed model outperformed the other models while proving the necessity of the data preprocessing step in the forecast. In further works we will focus on gathering high accurate data from multiple stations to get better results, trying with more LSTM variations in order to pick out the best one and compare it with other linear and nonlinear models while keeping up with trying other techniques for smoothing data.

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