Wind Turbine Prediction using Deep Learning and Long Short Term Memory (LSTM)

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Abstract

Accurate forecasting is essential for the long-term success of adding wind energy to the national power system. In this study, we look at forecasting wind turbine using a LSTM deep learning model. To forecast potential outcomes for a time series, it is sufficient to initially obtain pertinent details from past data. While many methods struggle with understanding the long-term dependencies encoded in data sets, LSTM options, an instance of the strategy in deep learning, show potential for efficiently overcoming this challenge. An overview of LSTM's architecture and forward propagation method is provided initially. LSTM network is applied to the wind turbine prediction dataset. This dataset has 9 features and 6575 records. There are four performance matrices used to test the model. The four matrices are mean squared error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared error (RMSE). MAPE obtained the least error.

Keywords: Deep Learning; LSTM; Error; MSE; MAE; MAPE; RMSE; Wind Turbine.

1. Introduction

Wind power is one of the most rapidly expanding sectors of the clean energy sector in recent years. In the following thirty years, wind turbines might account for 18% of worldwide energy production. Downstream wind turbines in a wind farm may experience significant power losses due to the wake effect, reducing the farm's total electricity output. The efficiency of converting wind power in a massive wind farm may be significantly increased by better knowledge and forecast of turbine wakes. Thus, wake forecasting is crucial for effectively implementing a turbine farm[1]–[3].

Rapid developments in the methods used for collecting clean energy, spurred in part by governmental expenditures as well as recognition of global warming, have led to a rising share of these forms of energy in comparison to traditional ones (like petroleum and coal). To be more precise, turbines may be located either onshore (on the ground) or offshore (in water) to harness the energy of the wind[4]–[6].

Offshore wind farms are becoming more common for a number of factors, such as the fact that wind conditions are better and more consistent at sea, the ease with which bigger units can be moved and erected, the reduced possibility for visual disruption and conflicts of fascination, and so on. Keeping wind turbines operating at peak efficiency during

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their expected 20-25 year lifespan, however, might cost as much as 25% of the total offshore construction price[7]–[9].

During condition monitoring (CM), modifications to a wind turbine's functioning that might indicate a potential problem are tracked and recorded. Reduced O&M expenses are to be expected as a direct result of improved fault prediction made possible by a more solid CM system[10], [11]. Motion analysis, strain evaluation, thermography, and noise measurement are only a few examples of the kinds of observations and operational details on which CM methods have traditionally depended. chances for incorporated and in-depth CM analysis, where numerous kinds of data may promote updated trustworthy, inexpensive, and strong making choices in CM, have risen up as a result of current advances in sensors and communication structures, big data management, machine learning (ML), and enhancements in computing power[12]–[14].

lately, deep learning has garnered a lot of interest owing to the increased capacity it provides in modeling complex systems, and it has emerged as one of the major study fields in forecasting thanks to the swift growth of current computer resources for greater computational effectiveness. DL is a kind of ML that takes its cues from the architecture of the human brain to automatically learn complex, hierarchical sequences. There are primarily four deep architectures: Auto-encoders are often employed in network pre-training because they are a basic neural network that can learn effective ways to represent the input data in an unsupervised way[15], [16].

A feed-forward neural network with numerous hidden layers, the Deep Belief Network (DBN) may unearth buried data patterns. A Restricted Boltzmann Machine (RBM) and a trained perceptron are the two main components. Studying the cerebral cortex of humans led to the development of convolutional neural networks. It is designed to use convolution and pooling as consecutive procedures for obtaining high-level features. One such deep design is the Recurrent Neural Network (RNN), which can remember recent input patterns. Another attempt to solve the issue of preserving long-term memory is the Long Short-Term Memory (LSTM) system[17], [18].

2. Wind Turbine

Environmental concerns have shifted the energy revolution's focus towards renewable sources like wind and solar power. The use of solar power has expanded considerably in recent years. Since it has more resources and uses more efficient power generating technologies, wind power has garnered a lot of interest. According to the 2019 Global Wind Energy Development Report, the total installed capacity of wind turbines throughout the world will increase to 60,4 GW this year. Large-scale unmanaged wind power, due to the unpredictability and uncertainty of the wind, might impair the stability of the power system, when linked to the grid. Wind farm dispatch techniques, which are mostly based on average distribution and proportional distribution, are needed to meet the grid's power demand. Nonetheless, the wind collected by wind turbines varies at various sites in big wind farms due to the topography impact, wake effect, turbulence severity, and other influencing variables. Each wind turbine's power distribution in a wind farm has to be established according to its individual operating parameters, which necessitates the power forecast for each wind turbine, to prevent the instability of the power grid [1,4].

Both the physical method, which involves measuring and analyzing the physical quantity to obtain the wind speed data, and the statistical method, which involves gathering historical data from the Supervisory Control and Data Acquisition system of wind farms and fitting curves, have been used to predict wind power in the past. Few studies attempt to estimate the power of several wind turbines, whereas many concentrate on projecting the overall output of a wind farm or a single wind turbine.

3. Long Short Term Memory (LSTM) Networks

All recurrent neural networks (RNNs), which include LSTM networks, have an "underlying architecture of inter-neuronal interactions includes at least one cycle," as defined by the researchers. Hochreiter and Schmidhuber developed them, and other authors like Gers and Schmidhuber developed them. Long short-term memory (LSTM) networks are optimized for learning long-term dependencies and have the ability to circumvent the shortcomings of RNNs, such as disappearing and ballooning gradients[19]–[22].

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A long short-term memory (LSTM) network has three levels: an input level, a hidden level(s), and an output level(s). Equivalent to the number of parameters that explain (feature area), the count of neurons in the input layer. The quantity of neurons in the output layer corresponds to the dimensions of the output space; here, we have two neurons that indicate whether or not a stock's performance is better than the cross-sectional midpoint. The so-called memory cells that make up the LSTM networks' hidden layer(s) are the systems' defining features. Every memory cell contains a forget gate (f_t), an input gate (i_t), and an output gate (o_t) that work together to keep the condition of the cell st stable. In Figure 1 we see a schematic of a memory cell and its internal workings[23], [24].

Every one of the 3 gates receives the output h_t of the memory neurons at the prior timestep in addition to the input x_t (one member of the input series) at every phase t. In this way, the gates serve as filters for their respective functions:

The forget gate controls what parts of the cell state are forgotten. The input gate determines what data is appended to the current state of the cell. The output gate controls what data of the cell condition is sent.

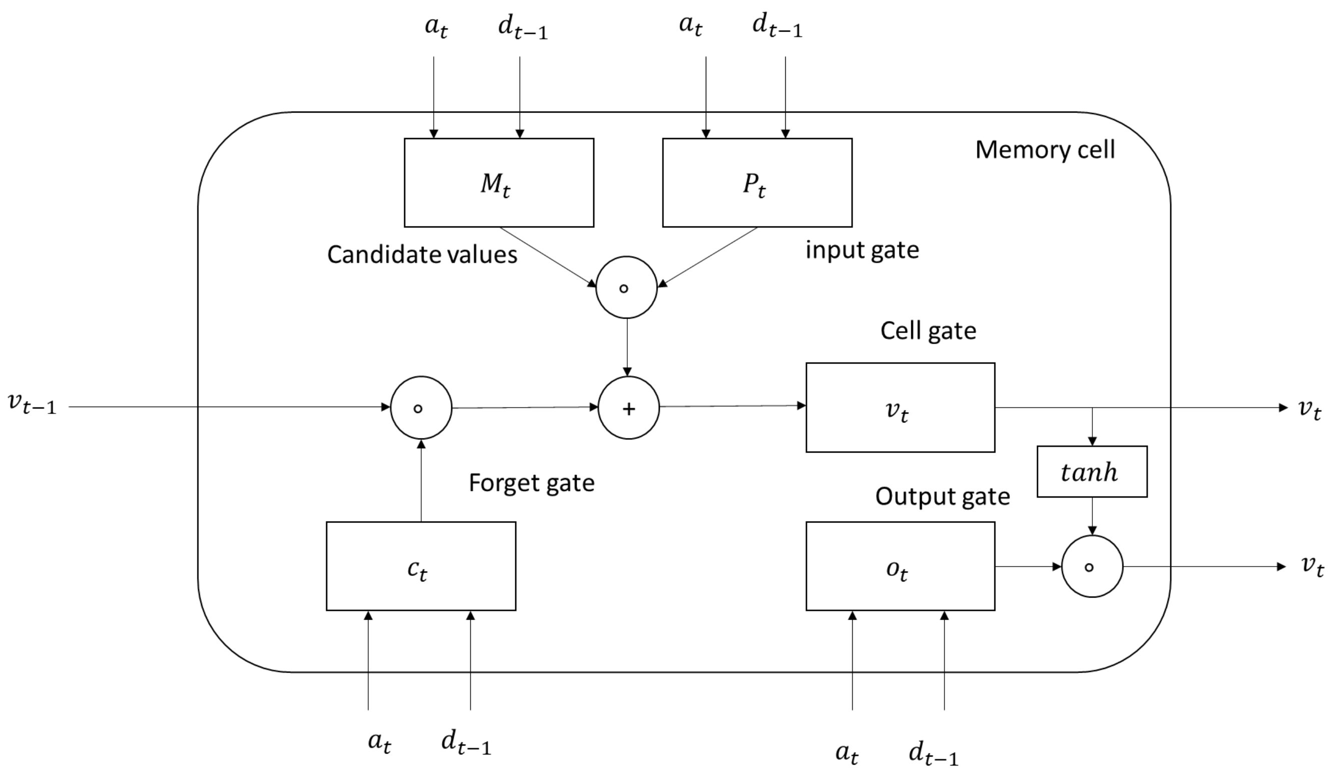

Figure 1: The design of the LSTM network.

There are equations to update the memory cell as:

$$\begin{pmatrix} a_t \quad is\ an\ input\ at\ t\ time \\ E_{c,a}, E_{c,d}, E_{v,d}\ are\ weight \\ k_f, k_v and\ k_0\ are\ bias \\ v_t \quad is\ an\ state \\ d_t \quad is\ a\ hidden\ function \\ u_t \quad is\ a\ output\ function \end{pmatrix}$$

The following are steps of the LSTM:

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1. Initially the LSTM layer decides what data should be omitted from the stored properties of the preceding cells v_t

$$C_t = G(E_{c,a}, a_t + E_{c,a}, D_{t-1} + K_C) \quad (1)$$

Where G is a sigmoid function

2. Compute information to be added in the state v_t

$$M_t = \tanh(E_{M,a}a_t + E_{M,d}d_{t-1} + k_M) \quad (2)$$

$$P_t = G(E_{P,a}, a_t + E_{P,a}, D_{t-1} + K_P) \quad (3)$$

3. Compute the new state based on previous two steps as:

$$v_t = c_t \circ v_{t-1} + P_t \circ M_t \quad (4)$$

4. Compute the output of the memory

$$u_t = G(E_{o,a}, a_t + E_{o,a}, D_{t-1} + K_o) \quad (5)$$

$$d_t = u_t \tanh(v_t) \quad (6)$$

4. Results

This section discusses the results of the LSTM network for wind turbine prediction. First we gathered the wind turbine dataset from Kaggle website. The dataset contains 6575 rows and 9 columns. The features are date, wind, IND, rain, ind.1, ind.2, T.MAX, T.MIN, and T.MIN. G. the sample of the dataset is presented in Table 1. Where WTP1 is a feature 1 and WTA1 is the row 1. The first column refers to the Date. This column is transformed to timestamp.

Table 1: The wind turbine prediction dataset.

	WTP1	**WTP2**	**WTP3**	**WTP4**	**WTP5**	**WTP6**	**WTP7**	**WTP8**	**WTP9**
WTA1	1/1/1961	13.67	0	0.2	0	9.5	0	3.7	-1
WTA2	1/2/1961	11.5	0	5.1	0	7.2	0	4.2	1.1
WTA3	1/3/1961	11.25	0	0.4	0	5.5	0	0.5	-0.5
WTA4	1/4/1961	8.63	0	0.2	0	5.6	0	0.4	-3.2
WTA5	1/5/1961	11.92	0	10.4	0	7.2	1	-1.5	-7.5
...	...	...	...	...	...	...	...	...	...
WTA6569	12/27/1978	14.46	0	16.8	0	9.8	0	4	0
WTA6570	12/28/1978	14.33	0	16	0	9.1	0	8.5	8
WTA6571	12/29/1978	19.17	0	14.7	0	5	0	3.5	3.2
WTA6572	12/30/1978	18.08	0	4.9	0	2.9	0	0.3	-0.5
WTA6573	12/31/1978	19.25	0	0.5	0	1.2	1	-1.5	-3

Then we show some representation of dataset into graph. We plot the date with the wind feature as shown in Figure 2.

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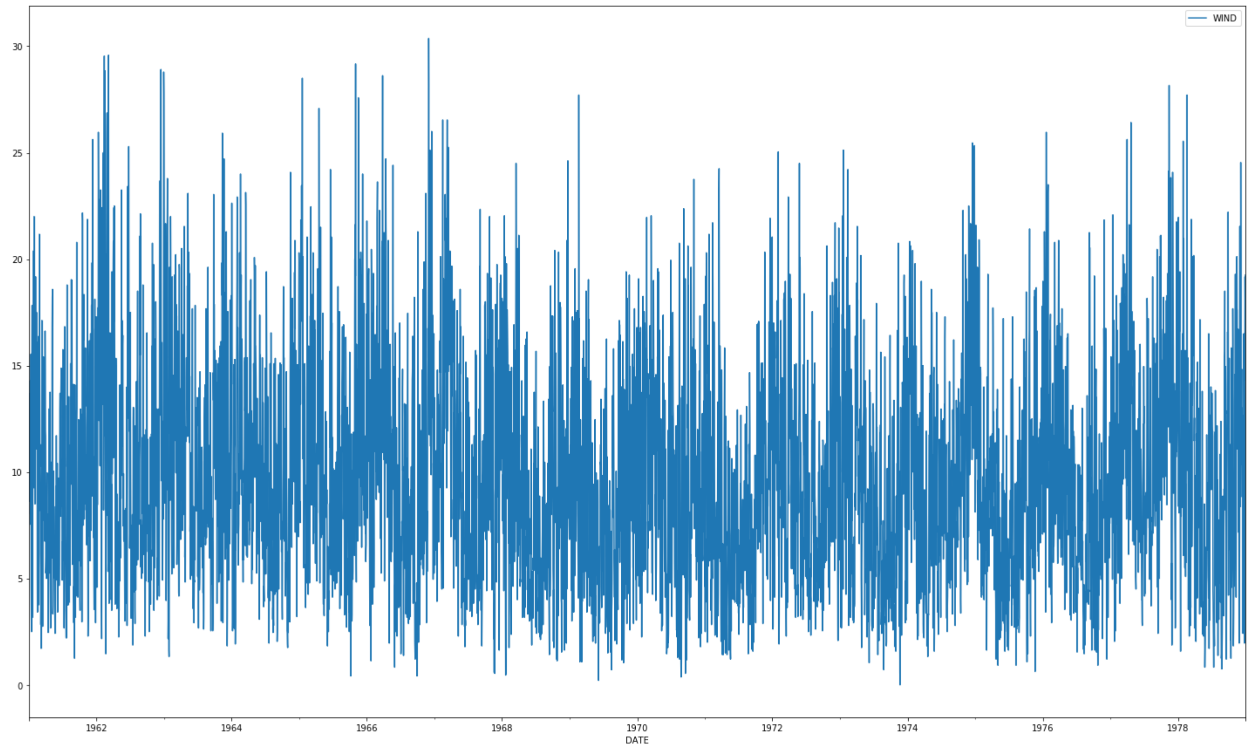

Figure 2: The plot between date and wind features.

Then we compute the correlation between features. So, we obtain the heatmap to show connection between variables and target variable.

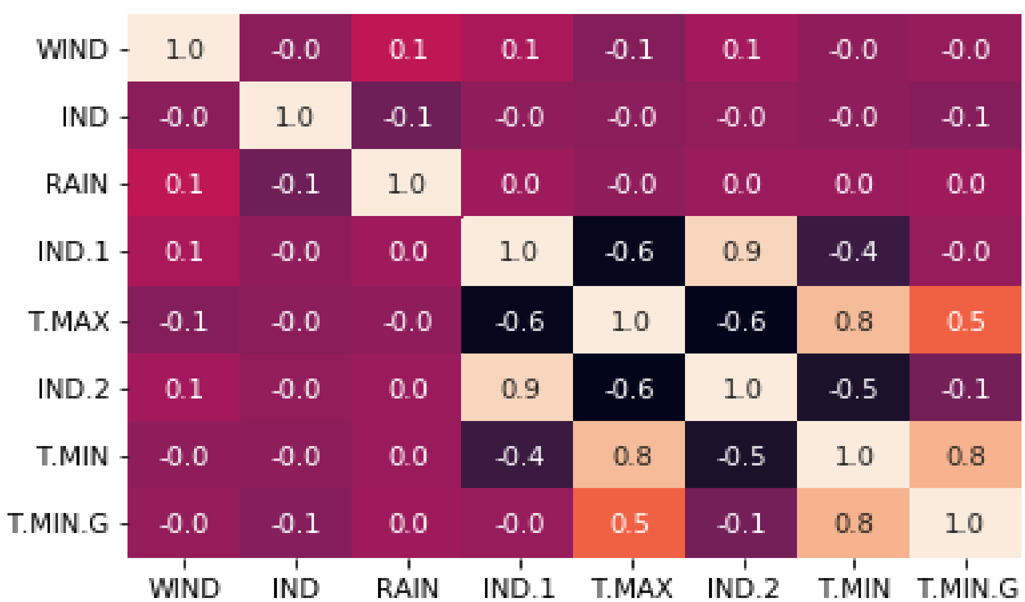

Figure 3: The correlation between features.

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We plot the data between all variables as shown in Figure 4.

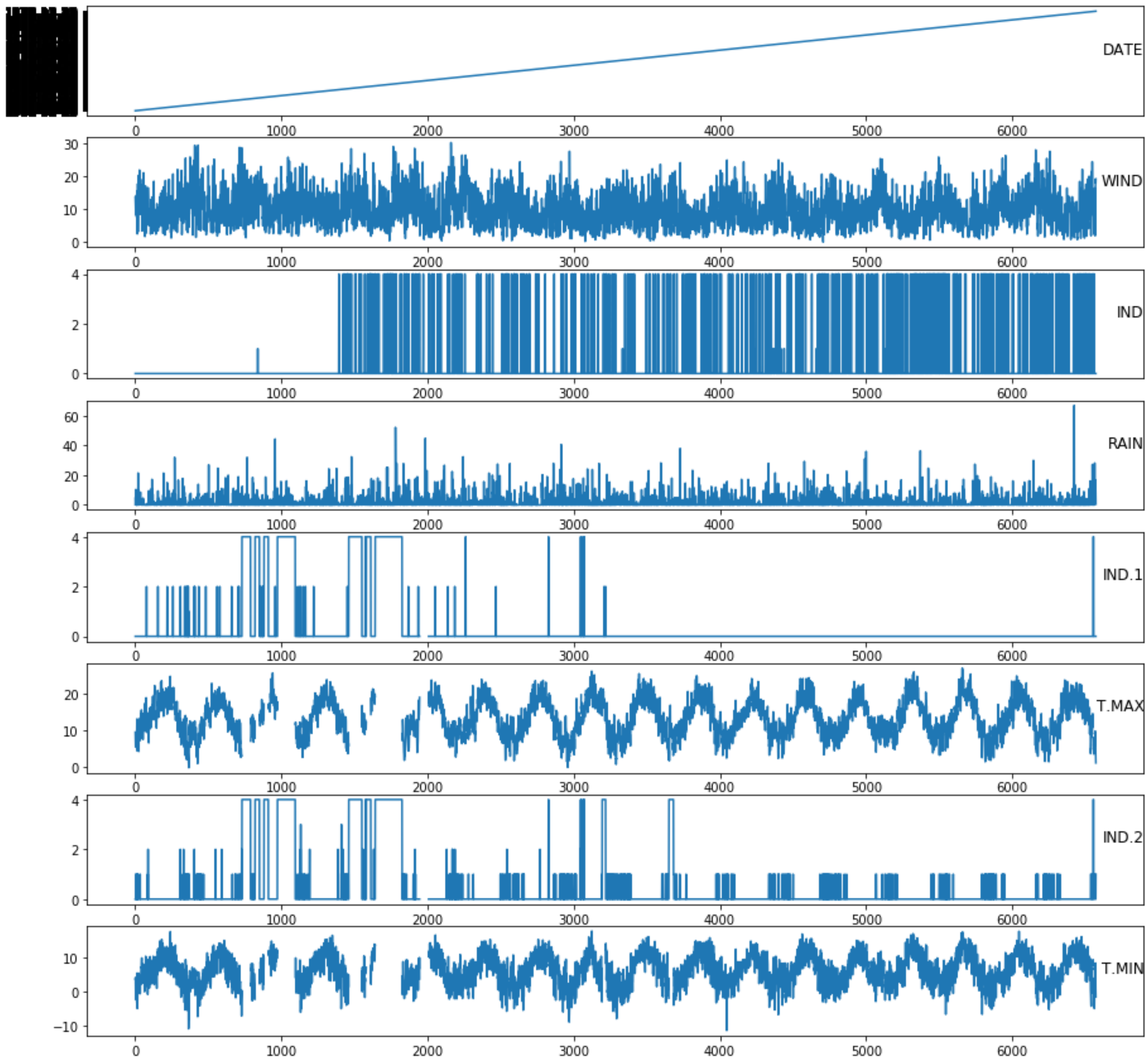

Figure 4: The distribution of the dataset.

Then we applied the proposed method into a dataset. Figure 5 shows the proposed method. We gather dataset, then we divided into a train and test. Then we used the LSTM networks to predict win turbine. We used the input layer and LSTM with 100 neurons, then follows by repeat vector. Then follows by double LSTM layer with 100 neurons. Then we used the time distributed. The we compiled the model with Adam optimizer and four evaluation matrices. These matrices are mean squared error, mean absolute error, mean absolute percentage error, and root mean squared error. Then fit model with 25 epochs and 32 batch size. Then we tested model to obtain the value of evaluation matrices as shown in Table 2.

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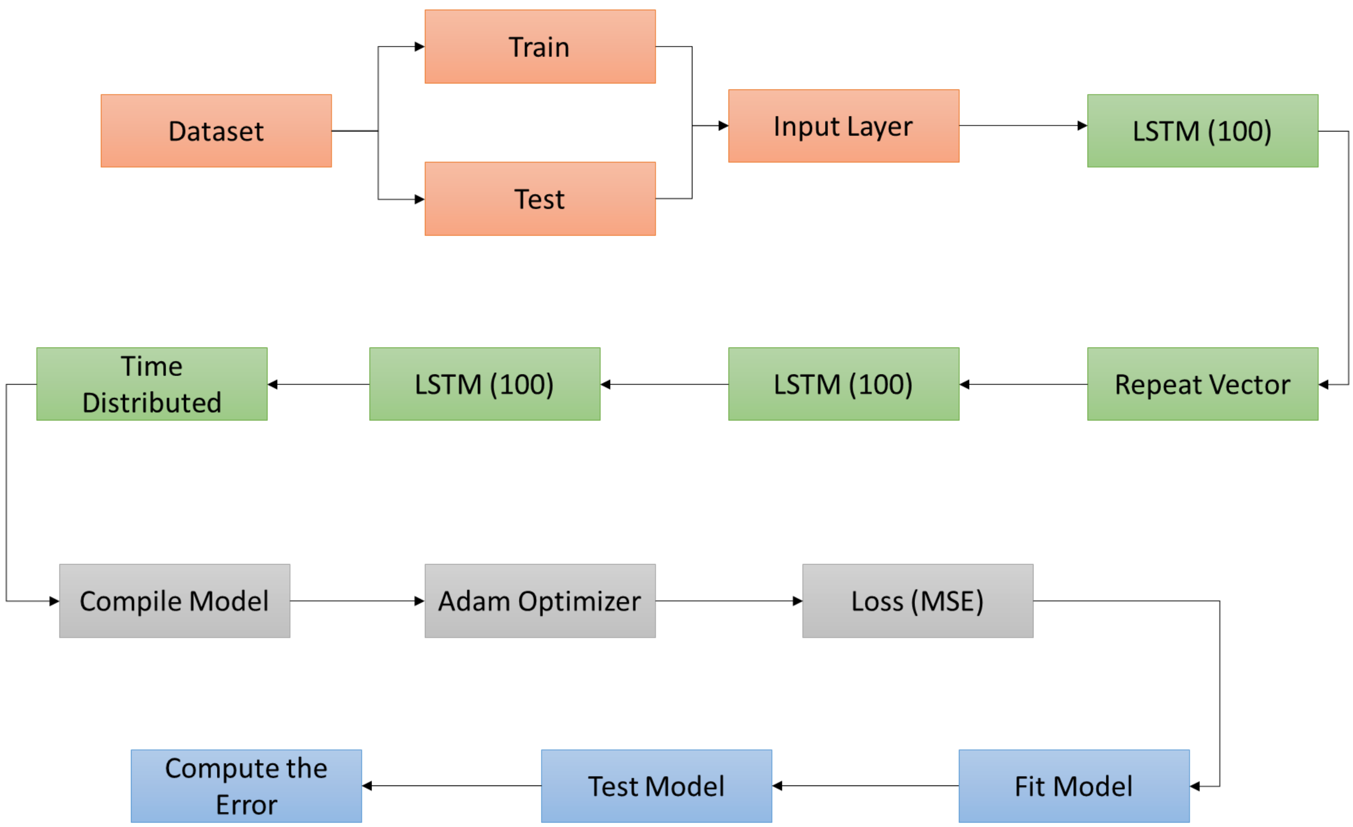

Figure 5: The proposed method.

We compared the proposed mole with four evaluation errors. We obtained the errors for nine features with five days.

Table 2: The evaluation variables.

	MAE	MSE	MAPE	RMSE
		Date		
Day 1	3.20E+16	1.53E+33	0.144829	3.91E+16
Day 2	3.75E+16	2.05E+33	0.169609	4.53E+16
Day 3	3.84E+16	2.18E+33	0.17287	4.67E+16
Day 4	4.15E+16	2.50E+33	0.186967	5.00E+16
Day 5	4.56E+16	2.93E+33	0.206476	5.42E+16
		Wind		
Day 1	3.32824	17.3296	1.52E+13	4.162884
Day 2	3.73451	21.54252	1.91E+13	4.641392
Day 3	3.861884	22.79465	1.65E+13	4.774374
Day 4	3.925243	23.37551	1.47E+13	4.834823
Day 5	3.96591	23.76116	2.14E+13	4.874542
		IND		
Day 1	0.992439	2.276722	1.8E+15	1.508881
Day 2	0.986991	2.306581	1.74E+15	1.518743
Day 3	0.984243	2.314161	1.72E+15	1.521237

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Day 4	0.983681	2.322604	1.71E+15	1.524009
Day 5	0.979864	2.330806	1.69E+15	1.526698
	Rain			
Day 1	2.286896	16.93971	3.11E+15	4.115787
Day 2	2.352189	16.54526	3.55E+15	4.067587
Day 3	2.238121	16.62578	3.11E+15	4.077472
Day 4	2.219989	16.69864	3.06E+15	4.086396
Day 5	2.240599	16.85335	3.14E+15	4.105283
	IND.1			
Day 1	0.073322	0.03337	3.01E+14	0.182674
Day 2	0.046535	0.027985	1.81E+14	0.167288
Day 3	0.034772	0.026235	1.29E+14	0.161972
Day 4	0.03352	0.026156	1.23E+14	0.161729
Day 5	0.037072	0.026533	1.39E+14	0.162891
	T.MAX			
Day 1	1.83998	5.549303	6.77E+13	2.355696
Day 2	2.139851	7.569695	8.04E+13	2.751308
Day 3	2.309808	8.874737	8.65E+13	2.97905
Day 4	2.455787	9.958146	8.75E+13	3.155653
Day 5	2.555354	10.76593	8.68E+13	3.281148
	IND.2			
Day 1	0.144412	0.074042	3.99E+14	0.272107
Day 2	0.130761	0.096468	2.4E+14	0.310592
Day 3	0.136466	0.107299	2.4E+14	0.327566
Day 4	0.134704	0.1106	2.25E+14	0.332565
Day 5	0.135858	0.114466	2.26E+14	0.338328
	T.MIN			
Day 1	2.185105	7.026884	4.63E+13	2.650827
Day 2	2.391581	8.577144	5.53E+13	2.928676
Day 3	2.542674	9.91301	9.43E+13	3.148493
Day 4	2.632571	10.76092	9.88E+13	3.280384
Day 5	2.720196	11.50994	1.04E+14	3.39263
	T.MIN.G			
Day 1	3.216003	15.99248	6.4E+14	3.999059
Day 2	3.771514	22.03585	7.08E+14	4.694236
Day 3	4.02282	25.13053	7.62E+14	5.013036
Day 4	4.161328	27.02828	8.05E+14	5.198873
Day 5	4.270921	28.48946	8.23E+14	5.337552

5. Conclusion

Only a forecasting system that produces a valid forecast error and is sufficiently effective to calculate the forecasts in a reasonable amount of time will allow wind power to be incorporated into the electrical system. This paper proposed the LSTM for wind turbine prediction.

In order to monitor the efficiency of fluid systems and forecast their RUL outputs, a deep learning-based method is presented. In particular, LSTM is studied to monitor system deterioration since it is a typical deep learning architecture effective at uncovering the discrepancy pattern underneath time series. A bidirectional LSTM network is designed to smooth the tracking and forecasting of results in the face of uncertainty caused by functional disruptions in the environment.

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This paper applied the dataset into nine features and 6575 records. This paper presented four performance matrices like MSE, MAE, MAPE, RMSE.

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