

Deep Wind - Predicting The Energy Output Of Wind Turbine Based On Weather Conditions.

IBM-Project-16393-1659613024

TEAM

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Problem statement

Deep Wind - Predicting The Energy Output Of Wind Turbine Based On Weather Conditions.



Extracting electricity from renewable resources has been widely investigated in the past decades to decrease the worldwide crisis in the electrical energy and environmental pollution.



For a wind farm which converts the wind power to electrical energy, a big challenge is to accurately predict the wind power in spite of the fluctuations.



The **energy output of a wind farm** is usually **dependent on the climatic conditions** present at its site.



For the wind farm operator, this poses difficulties in the system and energy planning, as the schedule of the wind power availability is not known in advance.



A **precise forecast** is needed to **overcome the problems** caused by **fluctuating weather conditions**.



Existing Solution

Wind power is calculated based on : **Physical characteristics of wind farms/turbines.**

$$Power = \frac{1}{2} \times \rho \times \pi \times r^2 \times C_p \times CF \times v^3 \times N_G \times N_B$$

P = power generated in Watts
v = velocity of the wind in m/s
 ρ = density of the wind in kg/m³
 πr^2 = swept area, where r = blade length in m
C_p = Power Coefficient
C_F = Capacity Factor
N_G = generator efficiency
N_B = gearbox efficiency

DISADVANTAGES:

- 👎 Measurement of wind turbine physical parameters (blade length, gearbox, generator) is quite difficult.
- 👎 Vary from turbine to turbine.



Proposed Solution

- 👍 Wind power is calculated based on : **weather conditions (wind speed, wind direction, pressure, temperature, dewpoint, relative humidity)**
- 👍 Our aim is to develop an end to end **web application** to predict **the energy output of the wind turbine based on weather conditions.**
- 👍 The technique incorporated in our project is **deep learning.**

ADVANTAGES:

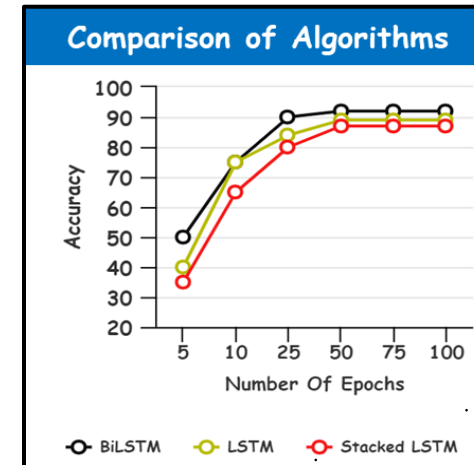
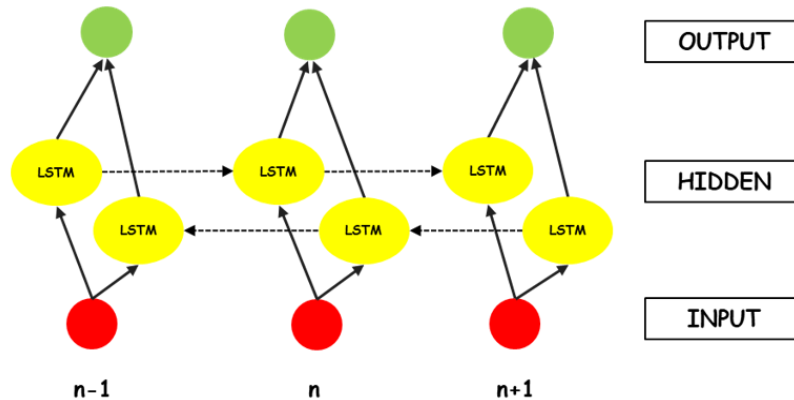
- 👍 **Rather than installing more devices on the turbine**, this idea can maximise yields and efficiency while having small effects on the climate.
- 👍 At the same time, it **boosts the performance and competitiveness of market players**, making this business more attractive.



Proposed Solution



Time series problems are mostly solved using RNN. These models have **memory**, i.e., the model can remember the information throughout the time.



A special kind of RNN – **BiLSTM Network (Bidirectional Long Short Term Memory)** is implemented which has a prominent performance in capturing the long-term dependencies along the time steps, and thus very applicable for wind power prediction.




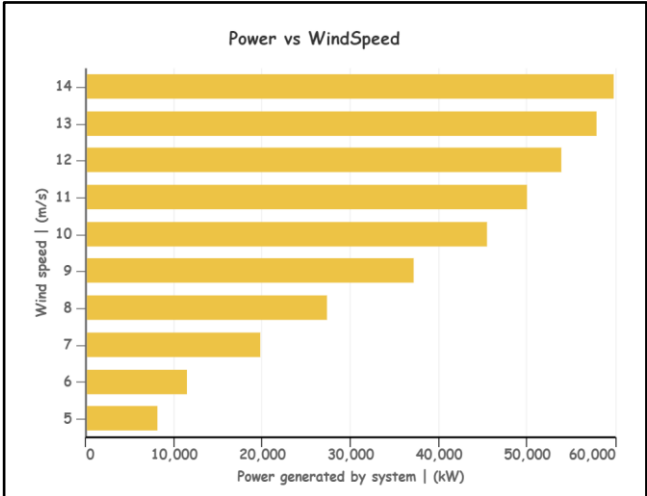




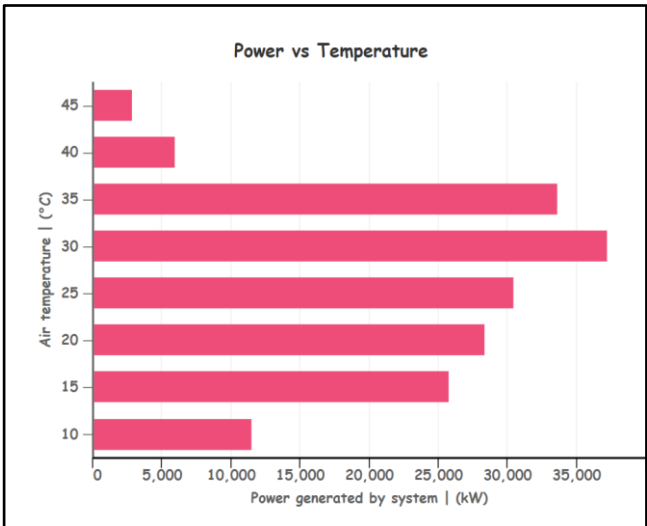
The proposed algorithm gave us more accurate results when compared with other models.

Motivation

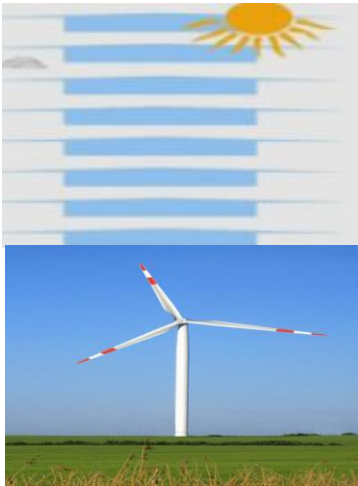
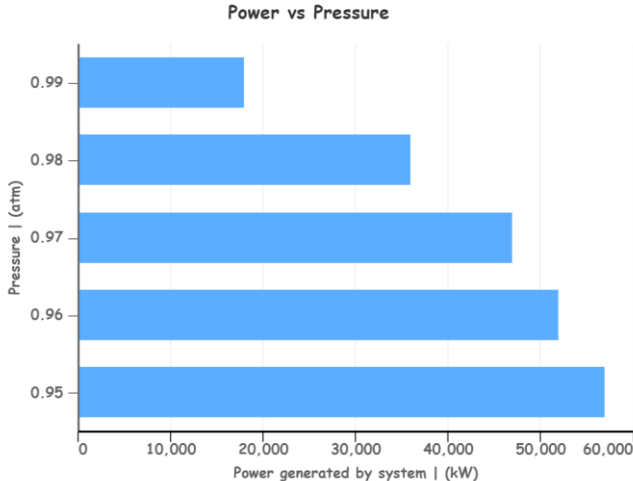
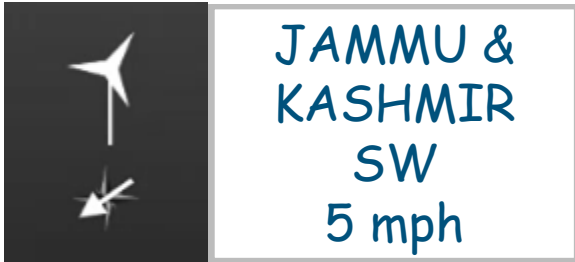
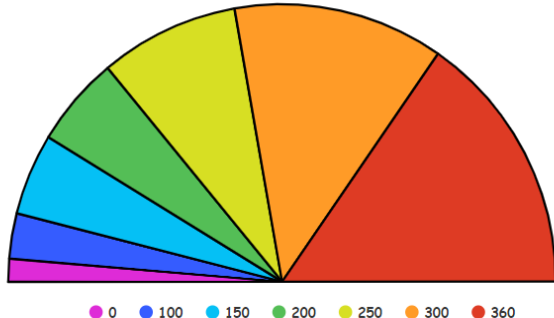
- ☀️ Since only very limited work has been done with respect to deep learning in the wind power prediction, it is of great interest to us to see how well it can perform in this field.
- ☀️ Through a combination of DL, computing and more accurate weather forecasts, granted access to more precise wind power data to **improve the efficiency of renewables**.
- ☀️ The forecasting process can also **save operators millions of dollars** in additional costs or fines for the mismatch between expected and actual production.



Metrics

PARAMETERS	VARIATION w.r.t POWER	GRAPH																						
<div>1. WIND SPEED</div> <div>Wind speed \propto Power generated</div>		 <table><caption>Power vs WindSpeed</caption><tr><th>Wind speed (m/s)</th><th>Power generated by system (kW)</th></tr><tr><td>5</td><td>8,000</td></tr><tr><td>6</td><td>12,000</td></tr><tr><td>7</td><td>20,000</td></tr><tr><td>8</td><td>28,000</td></tr><tr><td>9</td><td>38,000</td></tr><tr><td>10</td><td>48,000</td></tr><tr><td>11</td><td>52,000</td></tr><tr><td>12</td><td>55,000</td></tr><tr><td>13</td><td>58,000</td></tr><tr><td>14</td><td>60,000</td></tr></table>	Wind speed (m/s)	Power generated by system (kW)	5	8,000	6	12,000	7	20,000	8	28,000	9	38,000	10	48,000	11	52,000	12	55,000	13	58,000	14	60,000
Wind speed (m/s)	Power generated by system (kW)																							
5	8,000																							
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10	48,000																							
11	52,000																							
12	55,000																							
13	58,000																							
14	60,000																							
<div>2. TEMPERATURE</div> <div> Air temperature (high) \propto 1/Power</div> <div> Air temperature (moderate) \propto Power</div> <div> Air temperature (low) \propto 1/Power</div>		 <table><caption>Power vs Temperature</caption><tr><th>Air temperature (°C)</th><th>Power generated by system (kW)</th></tr><tr><td>10</td><td>12,000</td></tr><tr><td>15</td><td>26,000</td></tr><tr><td>20</td><td>28,000</td></tr><tr><td>25</td><td>30,000</td></tr><tr><td>30</td><td>32,000</td></tr><tr><td>35</td><td>33,000</td></tr><tr><td>40</td><td>6,000</td></tr><tr><td>45</td><td>4,000</td></tr></table>	Air temperature (°C)	Power generated by system (kW)	10	12,000	15	26,000	20	28,000	25	30,000	30	32,000	35	33,000	40	6,000	45	4,000				
Air temperature (°C)	Power generated by system (kW)																							
10	12,000																							
15	26,000																							
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25	30,000																							
30	32,000																							
35	33,000																							
40	6,000																							
45	4,000																							

Metrics

PARAMETERS	VARIATION w.r.t POWER	GRAPH																
<div>3. AIR PRESSURE</div> <div>Air Pressure \propto 1/Power</div>	<div></div> <div>High Pressure</div>	<div>Power vs Pressure</div>  <table><tr><th>Pressure (atm)</th><th>Power generated by system (kW)</th></tr><tr><td>0.99</td><td>18,000</td></tr><tr><td>0.98</td><td>36,000</td></tr><tr><td>0.97</td><td>47,000</td></tr><tr><td>0.96</td><td>52,000</td></tr><tr><td>0.95</td><td>58,000</td></tr></table>	Pressure (atm)	Power generated by system (kW)	0.99	18,000	0.98	36,000	0.97	47,000	0.96	52,000	0.95	58,000				
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0.96	52,000																	
0.95	58,000																	
<div>4. WIND DIRECTION</div> <div>Getting more nearer to 360° (north), wind speed increases, so severe winds blow from north generating more power.</div>	<div></div>	<div>Power vs WindDirection</div>  <table><tr><th>WindDirection (°)</th><th>Power (kW)</th></tr><tr><td>0</td><td>5,000</td></tr><tr><td>100</td><td>10,000</td></tr><tr><td>150</td><td>15,000</td></tr><tr><td>200</td><td>20,000</td></tr><tr><td>250</td><td>25,000</td></tr><tr><td>300</td><td>30,000</td></tr><tr><td>360</td><td>35,000</td></tr></table>	WindDirection (°)	Power (kW)	0	5,000	100	10,000	150	15,000	200	20,000	250	25,000	300	30,000	360	35,000
WindDirection (°)	Power (kW)																	
0	5,000																	
100	10,000																	
150	15,000																	
200	20,000																	
250	25,000																	
300	30,000																	
360	35,000																	

Impact

▪ BENEFIT TO BUSINESS & SOCIETY



Knowing the wind power beforehand helps us in many ways by minimizing the losses.



Target Audience:



Grid Operators



Energy Suppliers



It's easy for **grid operators**, in the case of **system scheduling** and **energy planning** for **power generating systems**.



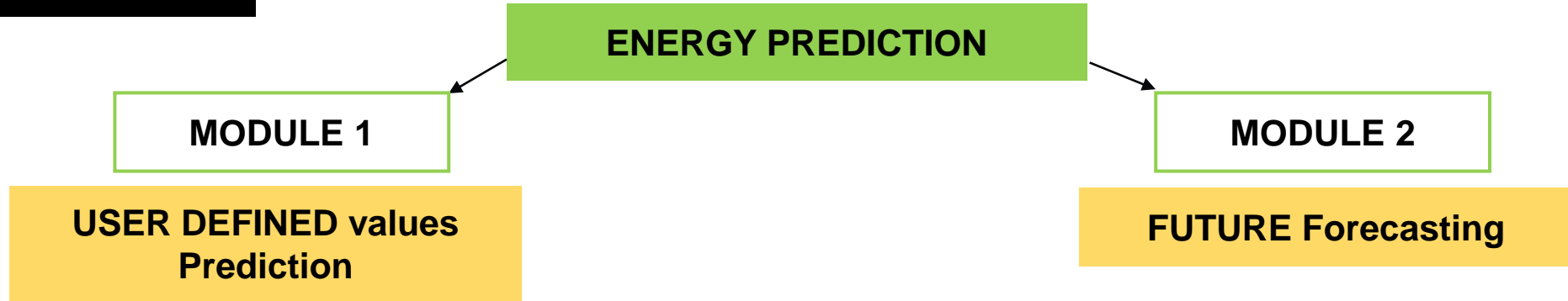
If the output may be forecasted extra accurately, **energy suppliers** can **keep away from costly overproduction** by coordinating the manufacturing of various electricity sources extra efficiently.



Thus accurate wind power forecasting plays a key role in **dealing with the challenges** of power system operation under uncertainties in an **economical and technical way**.

Methodology

Website Framework



Energy Prediction

Wind Speed (m/s)

Temperature (°C)

Pressure (atm)

Wind Direction (deg)

Predict

Predicted Power (kW)

City based Prediction

Enter the city:

coimbatore

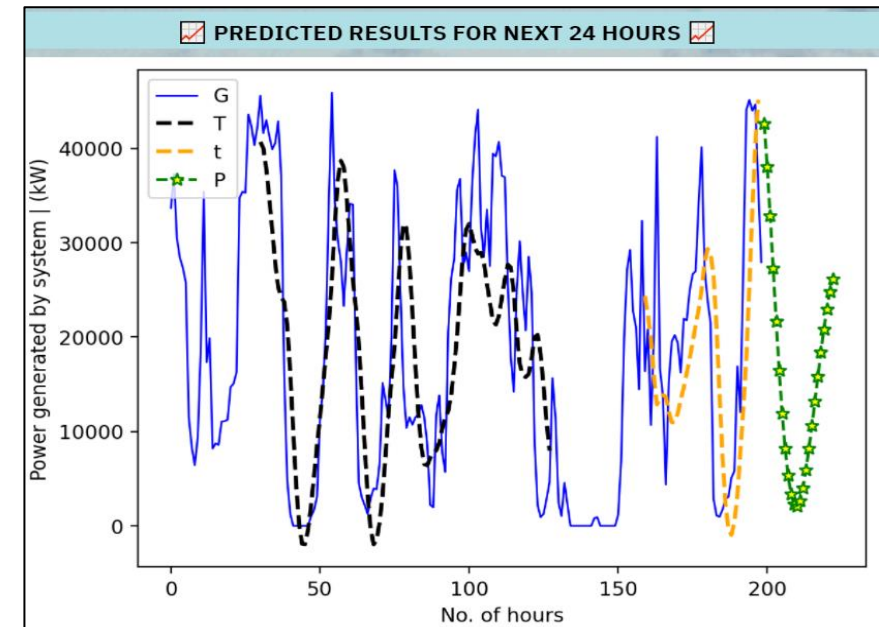
Wind Speed: 1.54

Wind Direction: 0

Air Temperature: 29.88

Air Pressure: 1010

Predicted Power is [[47.03291]] kW



Technology Stack

TECHNOLOGY STACK



FRONT-END WEB DEVELOPMENT

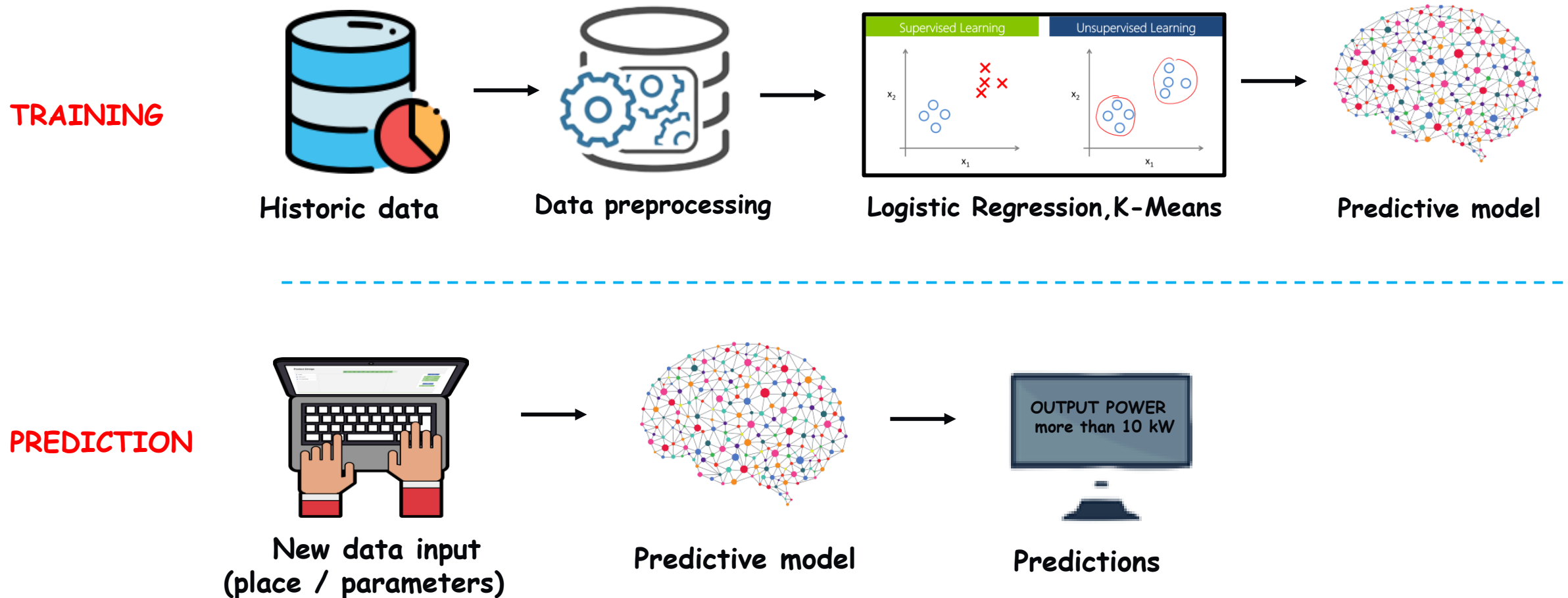


Pandas



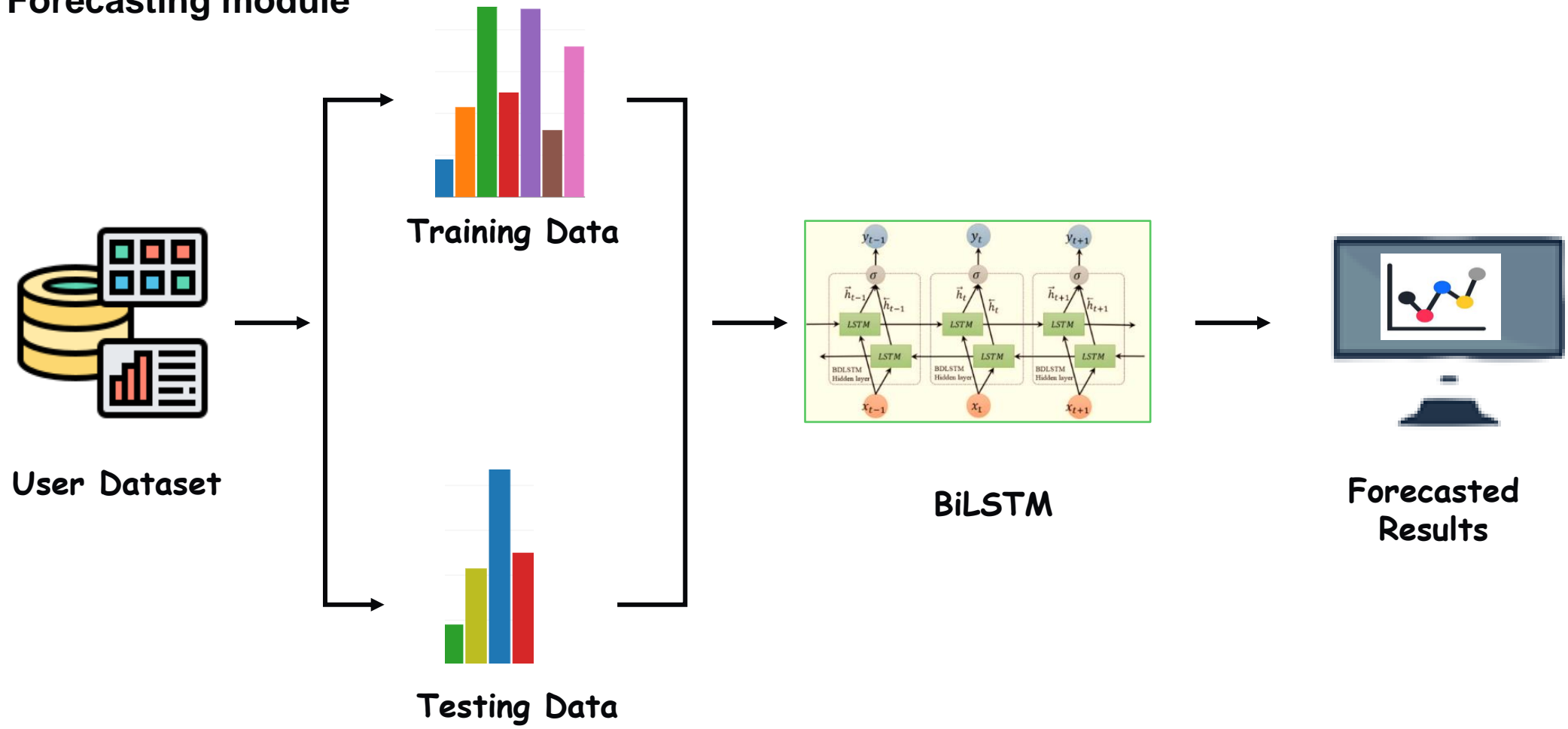
Architecture

Prediction module



Architecture

Forecasting module



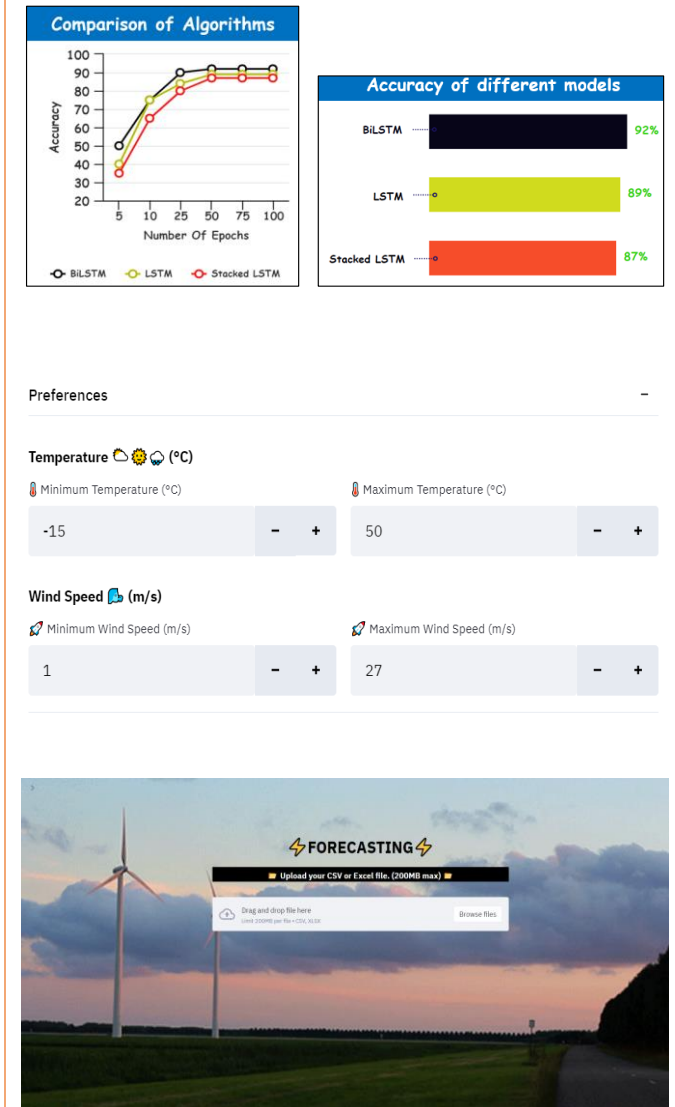
How is the solution innovative?

👍📈 **Bi-LSTM** gave us more accurate results when compared with other models.

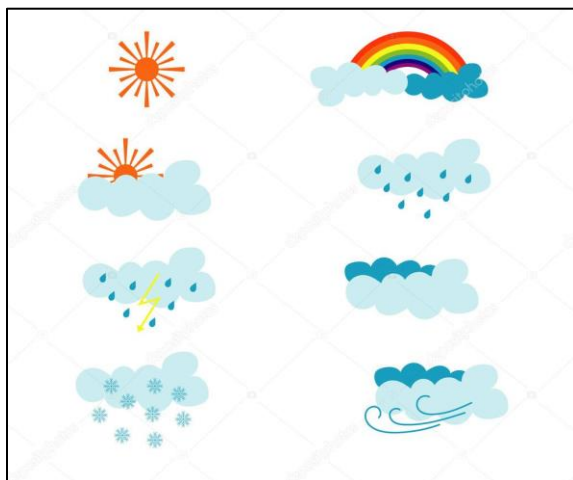
👍📈 In the prediction part, user can also set their preferable **cut in (minimum) and cut out(maximum) values** for windspeed and temperature with the help of **preferences tab**.

👍📈 Our Deep Wind is individually different from other wind power forecasting websites where the **user can upload their own real time dataset (csv or xlsx format with a minimum of 30 entries) for forecasting**.

👍📈 Our Deep wind provides an interactive interface with a **simple visualization tool** which brings the accurate results with minimal load time.



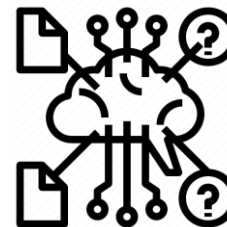
Link  : <https://share.streamlit.io/deep-wind/miniproject/main/app.py#deep-winds>



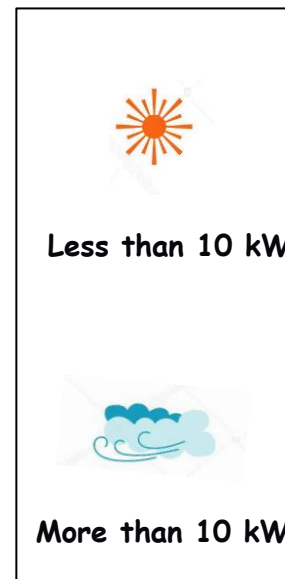
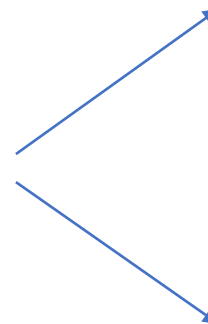
Unlabeled Data



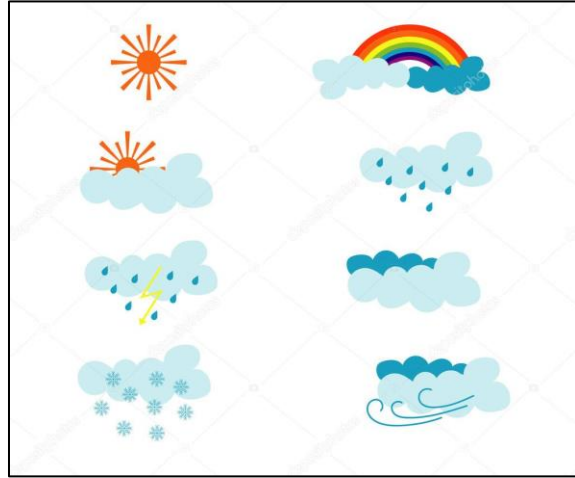
Interpret raw data



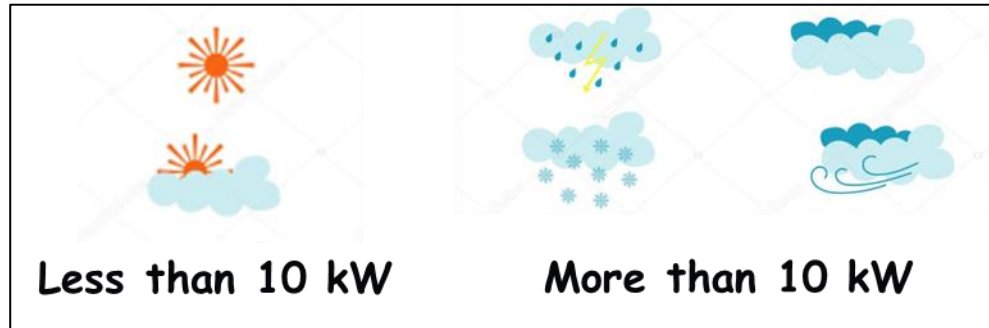
Processing



Output



Labeled Data

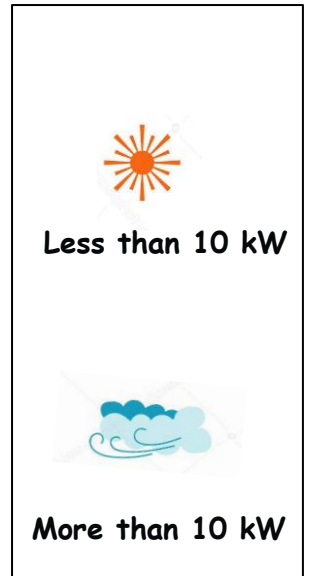
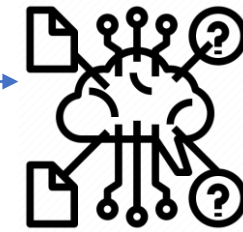


Labels

Training



Prediction



Output



Test data

PREDICTION	FORECASTING
CALCULATION/Estimation OF FUTURE PREDICTIONS With/without prior information	CALCULATION/Estimation OF FUTURE PREDICTIONS which uses trends in previous events, to come up with the future outcome.

BILSTM

I/P : 6

(wind speed, wind direction, pressure, temperature, dewpoint, relative humidity)

HIDDEN: 7

OUTPUT: 1

CODE

```
model = Sequential()
model.add(Bidirectional(LSTM(100, activation='relu',input_shape=(-1,1,6))))
model.add(Dense(7))
model.add(Dense(1))
model.compile(loss='mae', optimizer='adam',metrics=['accuracy'])
model.fit(X, Y,epochs=1,callbacks=[keras.callbacks.EarlyStopping(patience=5)])

test_data = np.array([[17.6, 940.4,4.08,101,8.1,60.1]])
print(model.predict(test_data.reshape(-1,1,6), batch_size=1))
o=model.predict(test_data.reshape(-1,1,6), batch_size=1)
print(o)
```



THANK YOU

