Application of Neural Networks to Enable Efficient Use of Wind Energy

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Introduction

- As fossil fuel resources get depleted and the issues relating to global warming become more prominent, there will be more of a need to transition to greener alternatives of energy production - Wind Turbines
- However, wind turbines have a very unstable way to power generation and thus require to be a part of larger energy system with other sources of power
- Proper use of wind turbines requires an ability to predict wind speed, so we can know when we can rely on it and when we should find alternatives for energy production

Research Question

Can we predict future wind speeds with neural network models that use the wind speeds measured and recorded in a past interval?

The Data

- Four years of data was collected from NOAA’s Integrated Surface Dataset
- We cleaned the data to focus only on hourly measurements, and focused on different variables for wind speed, temperature, solar radiation, and humidity

```
Index(['wnd_speed', 'temp_change', 'hourly_liq_depth_dim', 'liq_depth_dim',
       'fan_speed', 'fan_speed2', 'fan_speed3', 'rh_air_temp', 'rel_humiditiy',
       'min_hourly_air_temp', 'max_hourly_air_temp', 'std_hourly_air_temp',
       'std_hourly_humidity', 'air_temp', 'air_temp_2', 'air_temp_3',
       'std_hourly_air_temp_2', 'std_hourly_air_temp_3', 'wet1', 'wet2',
       'solar_rad', 'min_solar_rad', 'max_solar_rad', 'std_solar_rad',
       'surface_temp', 'std_surface_temp', 'ex_air_temp', 'ex_air_temp_2',
       'hourly_gust', 'wind_std', 'hour'],
      dtype='object')
```

Models

- We tried different regularizations, units, and depths, but these modifications did not add any significant improvement to model performance
- The final models we implemented are two LSTM models, predicting one hour and six hours ahead

LSTM model for 1 hour

```
model = Sequential()
model.add(LSTM(64, return_sequences=True,input_shape=(train_X.shape[1], train_X.shape[2])))
model.add(LSTM(units=32, return_sequences=True))
model.add(LSTM(units=16))
model.add(Dense(units=1))

model.compile(loss='mse', optimizer=keras.optimizers.Adam(learning_rate=0.001))
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm (LSTM)                  (None, 1, 64)             24576
_________________________________________________________________
lstm_1 (LSTM)                (None, 1, 32)             12416
_________________________________________________________________
lstm_2 (LSTM)                (None, 16)                3136
_________________________________________________________________
dense (Dense)                (None, 1)                 17
=================================================================
Total params: 40,145
Trainable params: 40,145
Non-trainable params: 0
```

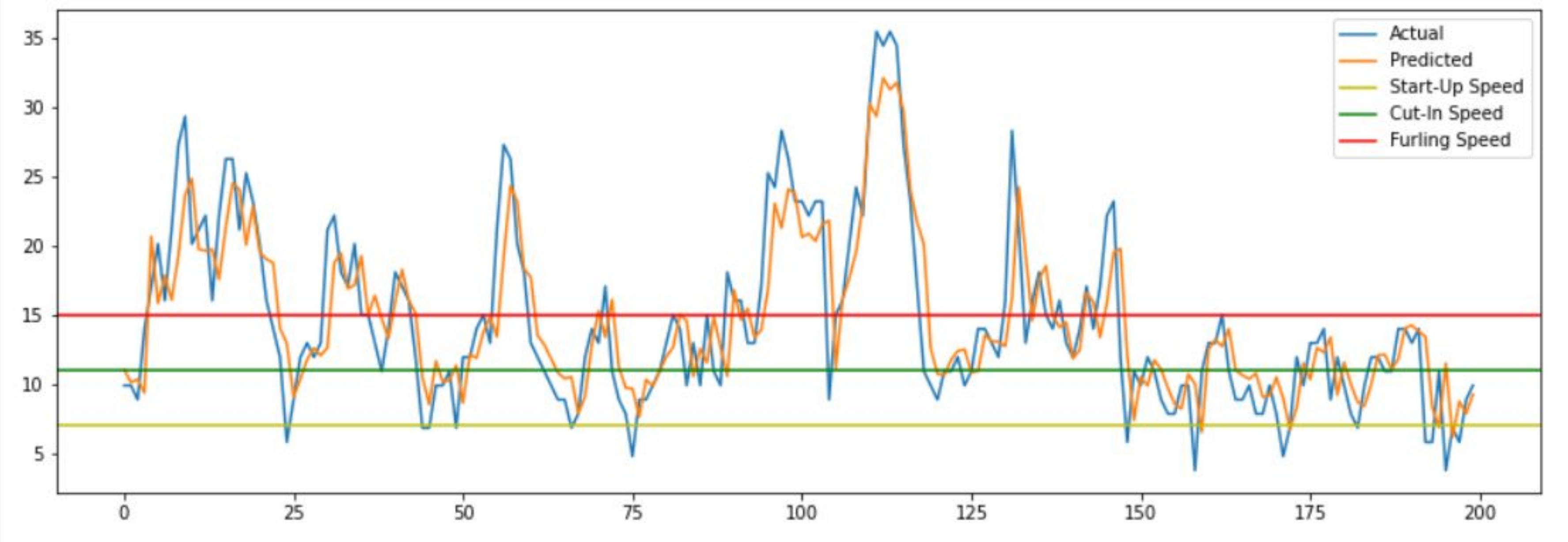
Results

Deep Learning Model MSE

0.3129

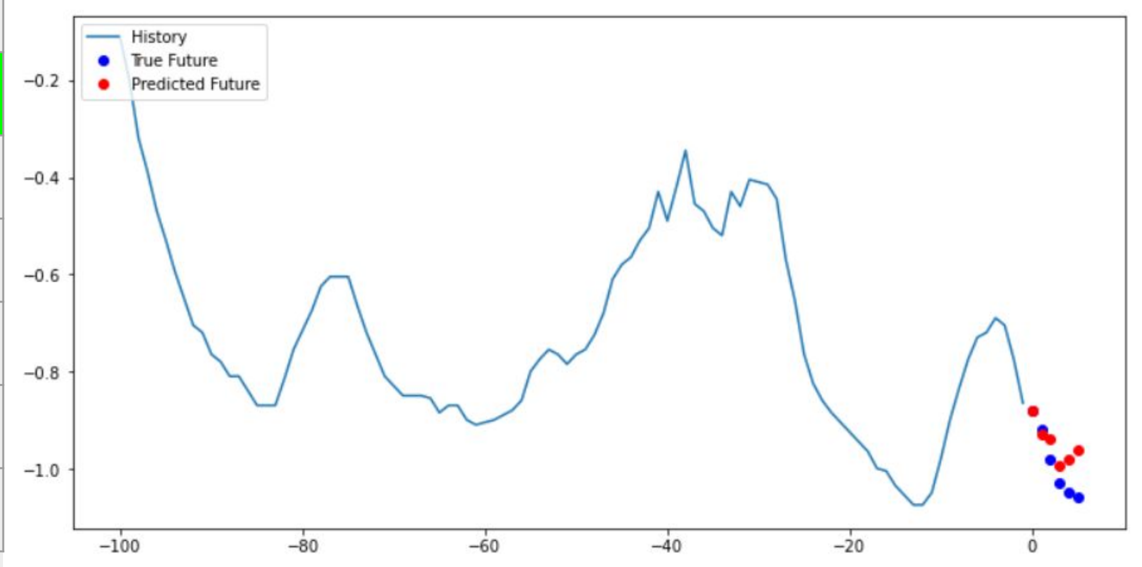
Persistent Model MSE

0.3227



Results

	LSTM	Persistent
1 hour	.0.410	.0245
2 hour	.0544	.0.666
3 hour	.0772	.1230
4 hour	.1004	.1886
5 hour	.1221	.2580
6 hour	.1479	.3272



Conclusion

- Wind can be predicted with a recurrent neural networks
- Marginally better 1 hour in the future
- Significantly better the further out the prediction