# Medium-term Wind Power Forecasting via Recurrent Neural Networks

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Wind energy will supply 35% of the nation's electricity in 2050. Accurate wind power forecasting is critical for the grid's efficiency, reliability, and sustainability. However, this task is challenging due to the high volatility nature of wind patterns. In this context, our goal is to design an efficient RNN framework that outperforms existing methods, which include persistence, ARIMA, polynomial regression, random forest, and SVR.

## DATA SET

**Dataset:** NREL Wind Integration National Dataset

- Consist of six-year data (2007 – 2012) sampled at 5-minute intervals for a single wind turbine.
- To account for the weather forecasting errors, truncated ±15% Gaussian noises are added to wind speed in the test set.

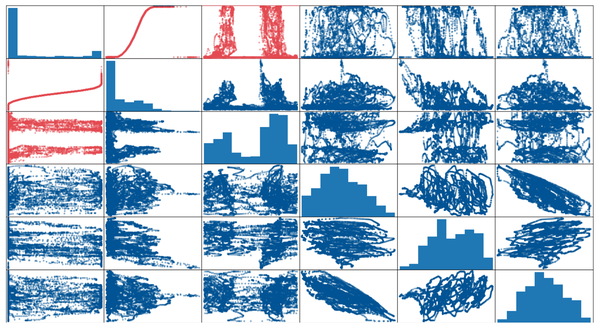

Figure 1: Feature selection via the scatter matrix: wind power, wind speed, wind direction, temperature, surface air pressure, and air density.

**Preprocessing and training**

- Predict power generation for the next 3 months by using 1 year training data with two features: wind **speed** and **direction**, chosen by the scatter matrix.
- Datasets are normalized prior to training.

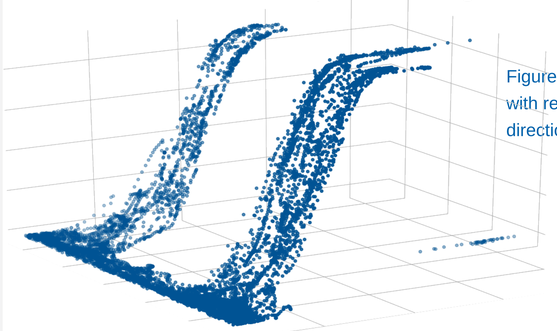

Figure 2: Wind power generation with respect to wind speed and direction.

## MULTILAYER PERCEPTRON NETS

**Overview:**

- Feed forward network with **unidirectional** flows (no memory).
- Use rectifier activation function.
- Trained using **backpropagation** and **adam optimizer**, which automatically adjusts the amount to update parameters based on adaptive estimates of lower-order moments.

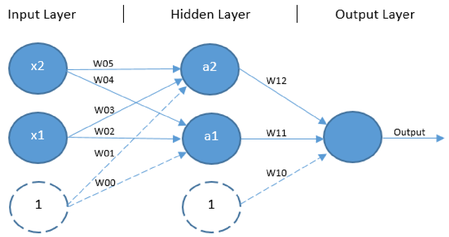


Figure 3: An MLP network consist of a single input and output layer, surrounding multiple hidden layers

**Hyperparameters:**

- Single hidden layer with 200 neurons.
- Learning rate: 0.0001.
- Mini-batch size: 200 (200 epochs).

## RECURRENT NEURAL NETS

**Overview:**

- Data can be fed back into the same and next layers allowing information to **persist.**
- Uses **LSTM** layers to control what information gets forgotten.

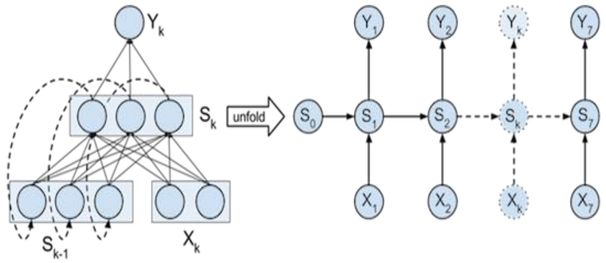


Figure 4: RNN structure

**Hyperparameters:**

- Two hidden LSTM layers: (7,5) units.
- Uses **rectifier** activation function, and **RMSProp** optimizer.
- Learning rate: 0.0001.
- Mini-batch size: 50 (250 epochs).
- Use the **mean squared error** loss function.

## SIMULATION RESULTS

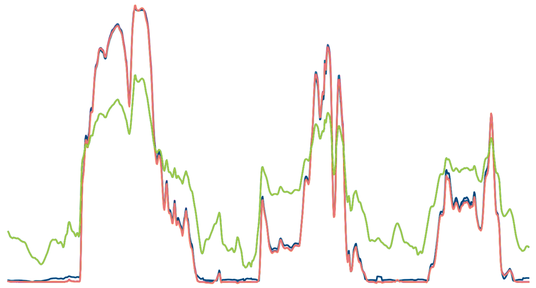

Figure 5: Results of 3 day forecasting with MLP (red), RNN (blue), linear regression (green), and ground truth (light blue).

Table 1: Average forecasting error with 100 Monte Carlo simulations.

| Method | MSE (true) | MSE (noisy) | MAE (true) | MAE (noisy) |
|---|---|---|---|---|
| Persistence | 0.2669 | 0.2669 | 0.3739 | 0.3739 |
| ARIMA | 0.1587 | 0.1587 | 0.2534 | 0.2535 |
| Linear regression | 0.0314 | 0.0322 | 0.1534 | 0.1540 |
| Poly. regression | 0.0043 | 0.0084 | 0.0488 | 0.0614 |
| SVR | 0.0034 | 0.0073 | 0.0365 | 0.0505 |
| Random forest | 0.0020 | 0.0056 | 0.0062 | 0.0365 |
| MLPN | 0.0012 | 0.0052 | 0.0079 | 0.0380 |
| RNN | 0.0011 | 0.0053 | 0.0063 | 0.0375 |

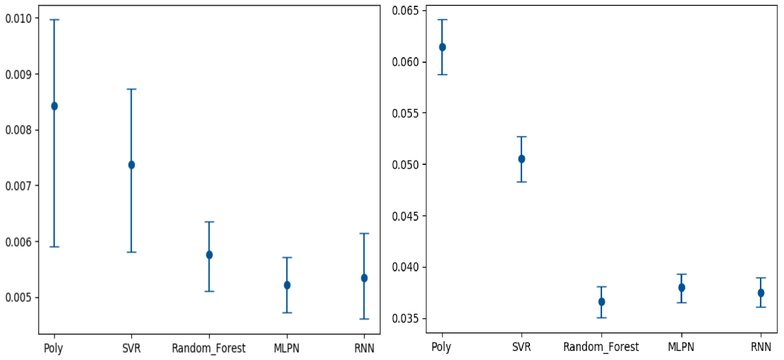


Figure 6: Forecasting errors based on 100 Monte Carlo simulations: MSE(left) & MAE (right).

## CONCLUSIONS

- RNN and MLPN are the best in terms of evaluating our model by MSE, while random forest also has a good performance.
- Next, we will build new RNN and MLPN models the short-term and long-term forecasting.
- We will extend the idea to predict solar power generation, load demand, as well as locational marginal prices.

**Neural networks improve the forecasting performance of renewable generation**

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