Wind Power and Electric Load Forecasting

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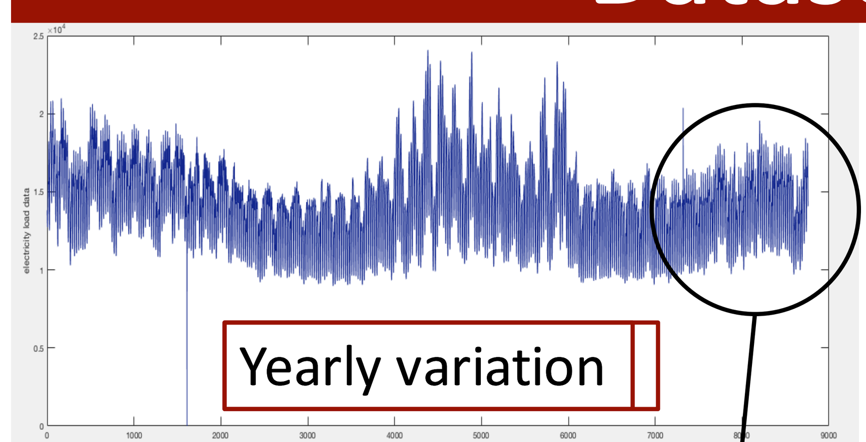
Motivation

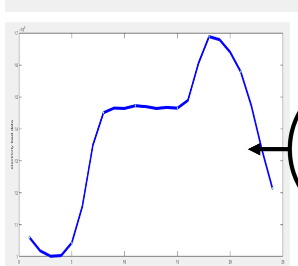
- Renewable energy integration is an essential branch of modern electric power system, and energy forecasting has been a fundamental task in electric power system.
- Forecasting both the electricity load and renewable power generation can provide guidance on energy strategy. Wind power generation is particularly difficult due to complex meteorological condition and local factors.
- The behavior of both electricity load and wind power generation can be modeled using different algorithms. Comparison between different models is necessary for the optimization of forecasting results and error minimization.

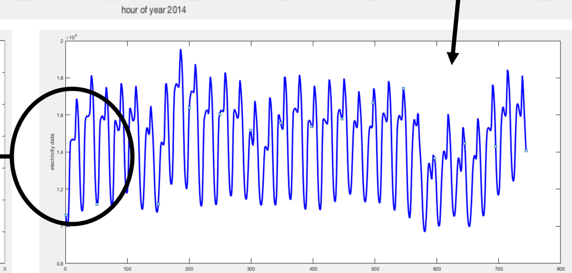
Main objectives

Efficiency improvement: Reduce the amount of training data without trade-off accuracy	Maximize performance: Focus on the points where the data show more complexity and harder to predict
Overall forecasting: Combine the load and wind forecasting to enhance economic performance	Combination of wind power generation forecast and electricity load prediction

Dataset

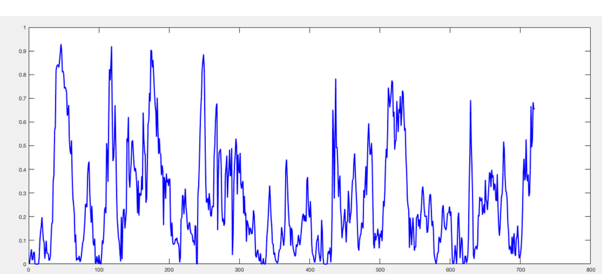


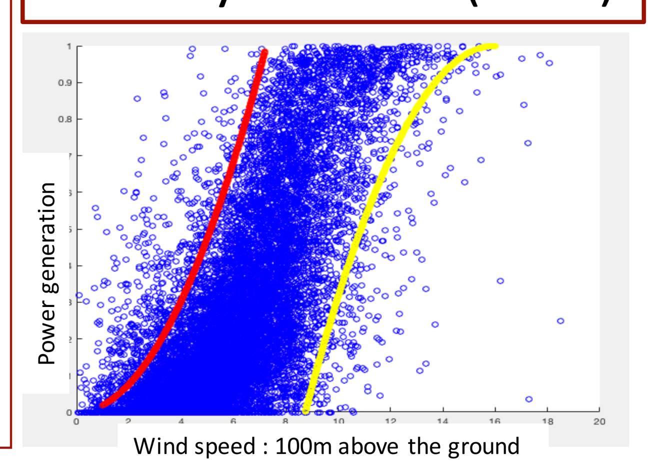




The hourly load and temperature data are collected from 2004 to 2014 (96432 data points in total). The data are available from ISO New England. The test data are selected in year 2014. Data from 2004 to 2013 are treated as training data base.

Hourly wind speed, direction and power generation data from 2012 and 2013 are collected. Three major differences between wind data and load data : 1)wind data have weak seasonal change. 2) wind data almost have no obvious periodicity. 3)wind data are more stochastic, with weak correlation with exterior variables, which calls for significant feature engineering.





Method

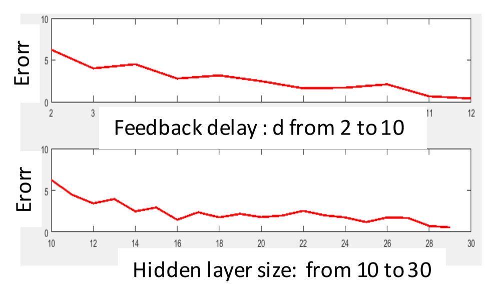
Autoregressive Neural Network

Autoregressive neural network is used in electricity load forecasting:

$$y(t)=\alpha_0+\alpha_1 y(t-1)+\lambda\tanh(\gamma(y(t-1)-c))+\varepsilon_t$$

$$y(t)=f(y(t-1),\dots,y(t-d))$$ (Without Temperature)

X(t) $$y(t)=f(x(t-1),\dots,x(t-d),y(t-1),\dots,y(t-d))$$



Error decreases with increasing hidden layer size (h) and feed back delay (d). But large h or d risk overfitting.

d and h are optimized to 4 and 10 respectively.

ARIMA

Arima model uses the data's own past value and past values of an error series to forecast future data.

Staple and stationary process:

- Autoregressive process (AR(p));
- Moving average process (MA(q));

Integrated nonstationary process:

- ARIMA(p,d,q)

ARIMA(1,1,2) represented by:

$$\hat{y}(t)=y(t-1)+\phi_1(y(t-1)-y(t-2))-\theta_1 e_{t-1}-\theta_2 e_{t-2}$$

Multivariate Linear Regression

Multivariate linear regression is simple and powerful method for forecast. The major challenge is to select appropriate predictors. A forward feature selection is applied in this project. Previous related neighbored value may also be considered as predictors for this project involving times series.

$$y_i=x_i\beta+\varepsilon_i$$

K Nearest Neighbor

K-Nearest Neighbors algorithm use k closest training samples to forecast wind power generation.

$$D(x_i,x_j)=\sum_{p=1}^{n_p} w_p * d\left(x_i^p,x_j^p\right)$$

Validation set is needed for choosing distance features and weights of each as well as value of k.

Result – Part I

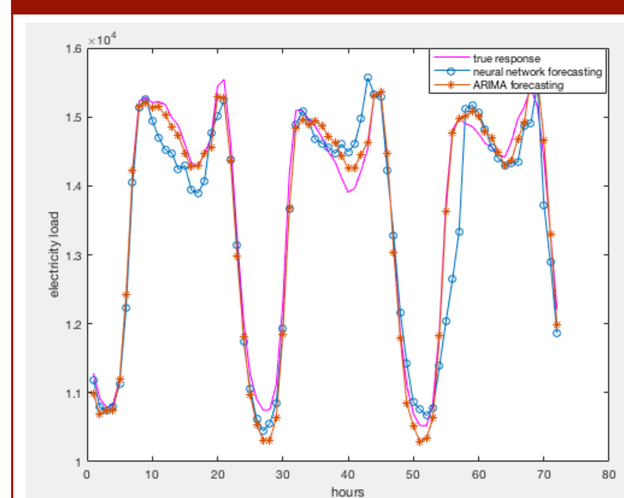
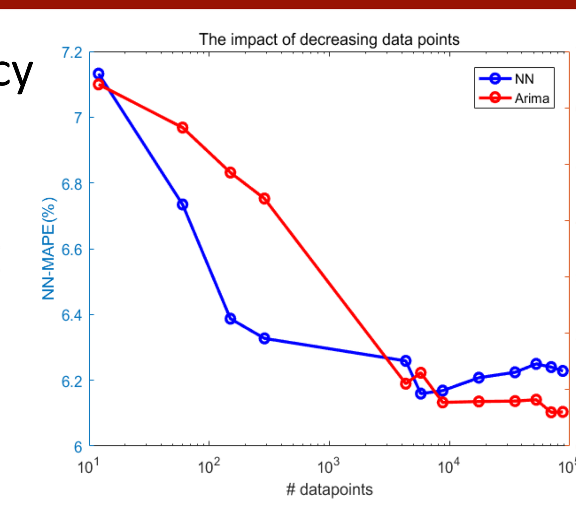


Figure1: original forecasting Using ARIMA and NAR forecast three days in 2014.

ARIMA is slightly better for short-term forecasting

Figure 2: Efficiency analysis. Relationship between training data size and MAPE.



Neural network is more efficient with limited training data size.

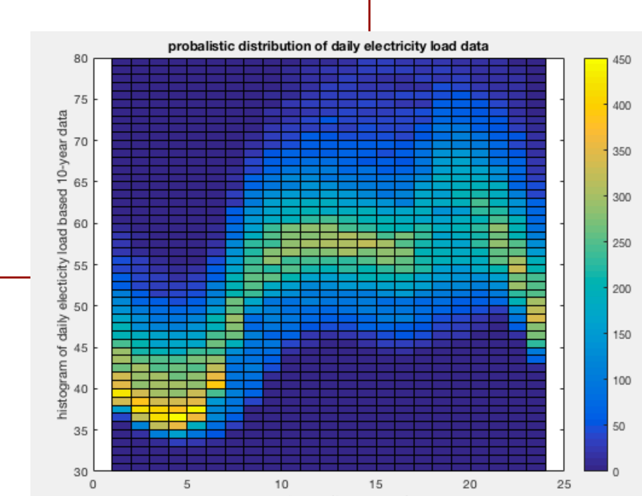
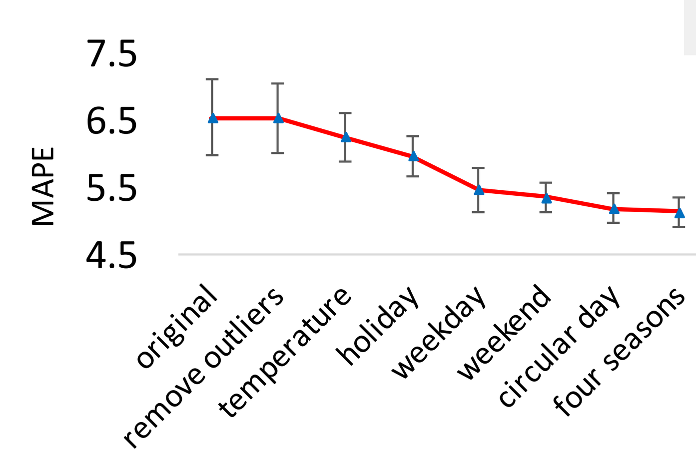


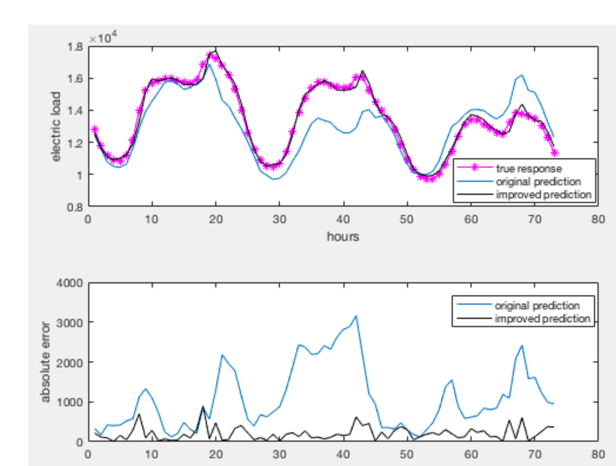
Figure 3: Feature engineering, one feature added each time.



Temperature, weekday and holiday have significant impact.

Performance improved after feature engineering.

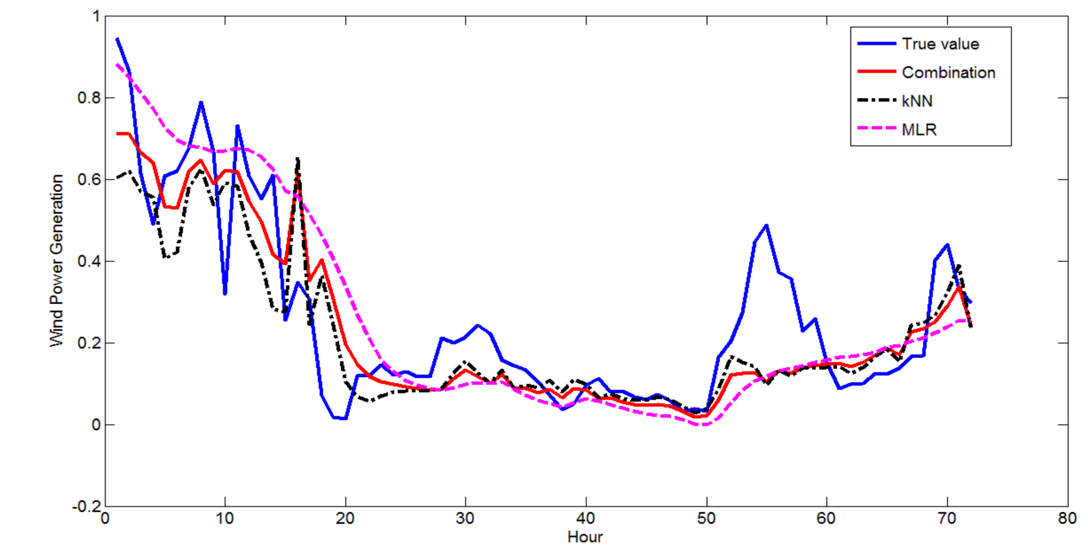
Figure 4: improve performance during Christmas (data more complex.



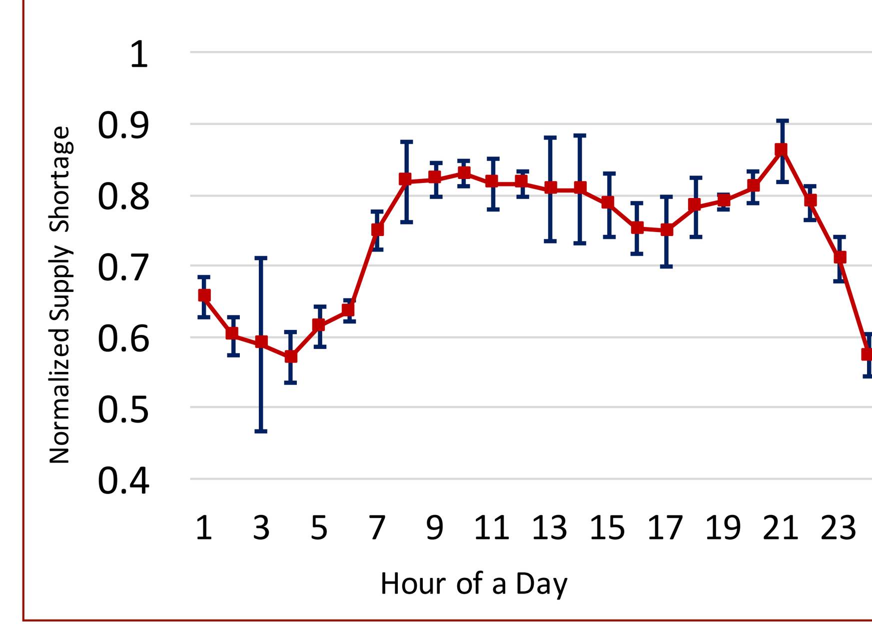
Result – Part II

Both MLR and kNN are applied to forecast wind power generation. For MLR, eight predictors are selected. For kNN, 100 closest training samples are used for forecasting and four predictors are used to calculate distance. A linear combination of these two methods with optimized weight equal to 0.61 is also used.

METHOD	RMSE
MLR	0.2170
kNN	0.2008
MLR+kNN	0.1967



Result – Part III



The left figure shows our forecasting of energy supply shortage, which is a combination of power generation forecasting and electricity load forecasting.

We have 95% confidence that the error of our estimation of energy supply shortage is less than 28.73%

Conclusion

1. Models with more complexity does not necessarily generate better performance. ARIMA is better at short-term forecasting, while NAR at long-term forecasting.
2. NAR is more statistically efficient when training data size is limited; Temperature, weekday and holiday are significant features; The performance of the model at where data are more complex was largely improved after feature engineering.
3. For wind power generation forecasting, KNN performs generally better than MLR, but boosting results demonstrated the combination of the two models can further improve the accuracy.

References

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