Probability Forecasting for Short Term Electric Load

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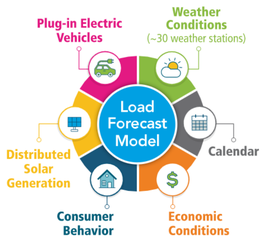
ABSTRACT

Electric Load forecasting has been playing a significant part for most of the operation and planning tasks in power systems for over a century. There are several crucial decision-making problems in power industry relying on the load forecasting. Hence, accurate and reliable load forecasting is critical for the decision-making processes. However, traditional point forecasting can not address the uncertainties and randomness of the real load power with one exact value. So far, the probabilistic forecasting techniques are greatly welcomed in the field of load forecasting for their capable of representing uncertainties.

In the final project, I used an *improved Quantile Regression Neural Network* to make the probabilistic forecasting of load more accurate and high efficiency.



INTRODUCTION

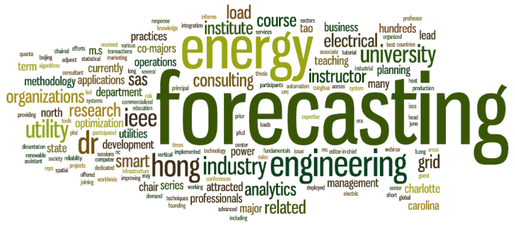
Problem Statement

In the project, we are trying to utilize the historical data of load power to train a model predicting the probability density of electric load power for the coming day which are greatly important for Day-ahead economic dispatch and unit commitment problems.

Datasets

Global Energy Forecasting Competition 2014 (GEFCom2014)

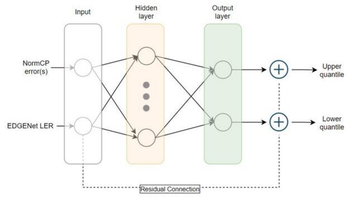
- 69 months of hourly load data
- 117 months of hourly temperature data
- Time info detailed to hours



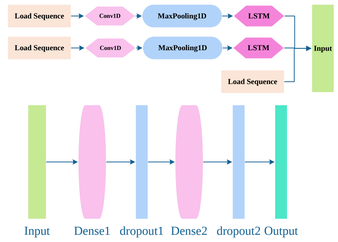
METHOD

An improved Quantile Regression Neural Network is proposed to address the weakness of traditional QRNN, which incorporates advanced techniques in deep learning areas.

Traditional QRNN



Improved QRNN



The traditional QRNN is very memory-consuming, time-consuming, low accuracy due to the its naïve structure and training scheme. In the proposed *Improved QRNN method*, we use the technique of CNN to make the structure more complicated to get a better result: we add 2 layers for Conv1D, Maxpooling1D and LSTM before the traditional QRNN which set the output of this structure to be the part of the new input layer.

In the QRNN part, we add dropout technique to prevent overfitting problems which randomly set a dropout ratio of neurons to be dead at each update during the training process.

To evaluate the result of the probabilistic forecast, two criteria methods are selected, quantile score and winkler score.

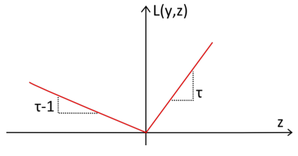
Quantile Score

$$L_{t,q}(q,\hat{y}_{t,q}) = \max\left(\left(\frac{q}{100}-1\right)(y_t-\hat{y}_{t,q}), \frac{q}{100}(y_t-\hat{y}_{t,q})\right)$$

$$QS = \frac{1}{\mathrm{card}(Q)\times T}\sum_{q\in Q}\sum_{t=1}^{T} L_{t,q}(q,\hat{y}_{t,q})$$

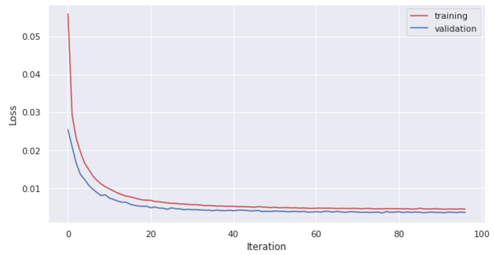
Winkler Score

$$WS = \begin{cases} \Delta_t & L_t \le y_t \le U_t \\ \Delta_t + 2(L_t - y_t)/\alpha & y_t < L_t \\ \Delta_t + 2(y_t - U_t)/\alpha & y_t > U_t \end{cases}$$

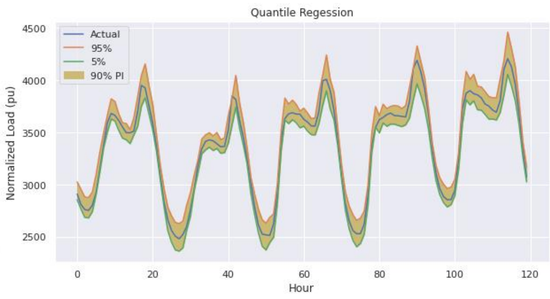


RESULTS

After 11.33 mins of training, the validation loss of the model stop improving from 0.00341 which means the best model of training was found. Actually, there is a little bit overfitting after the last few iterations, the best model should be around 40~60 epochs.



Curve of Loss



Result of Probabilistic Forecasting

WS of the testing set: 226.23

Training time taken: 11.33m

CONCLUSION

In this final project, an improved quantile regression neural network is proposed for probabilistic forecasting of electric load. The final result looked pretty well that the prediction interval almost completely cover the real value of load curve. Also, the difference between quantile 5% and quantile 95% is small which means the model give the meaningful probabilistic forecasting result. However, because of the time limitation and limited work by one person team, comparison of different models and parameters were ignored in the final project which can not show the outstanding performance of our proposed iQRNN model. It should be done in the future.

REFERENCE

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[3] W. Zhang, H. Quan and D. Srinivasan, ”An Improved Quantile Regression Neural Network for Probabilistic Load Forecasting,” in IEEE Transactions on Smart Grid, vol. 10, no. 4, pp. 4425-4434, July 2019, doi: 10.1109/TSG.2018.2859749.