Short-term Nodal Load forecasting for SCUC Based on Data Mining methodology

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I. INTRODUCTION

Our poster introduces an advanced method to predict Short-term Nodal Load data in power system. This method forecasts a set of load profiles for the next day which can cover minor changes. Data Mining (DM) techniques are heavily used to deal with the existing historical data. Least absolute shrinkage and selection operator (LASSO) is employed to reduce the number of features for a single nodal load forecasting. Principal component analysis (PCA) is used to capture the features of the historical load in low dimensional space compared to the original high-dimensional load space, whose feature is hard to describe. Bayesian Ridge Regression (BRR) is employed to form the prediction model which is sophisticated method to decide the parameters in the model from statistical point of view.

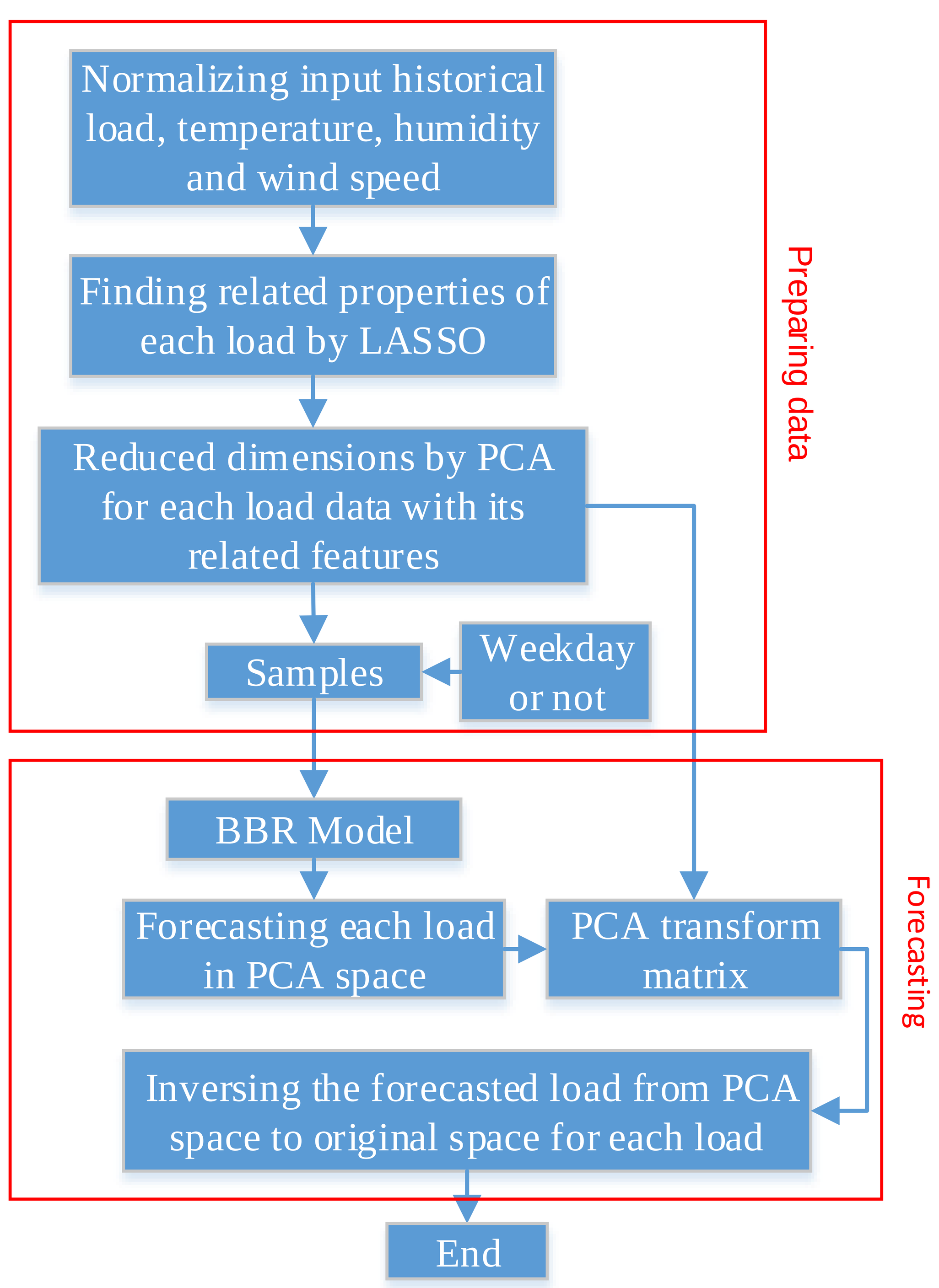

Fig. 1Flowchart of application for STNLF

II. SOLUTION OF STNLF

Data source: PJM zonal data

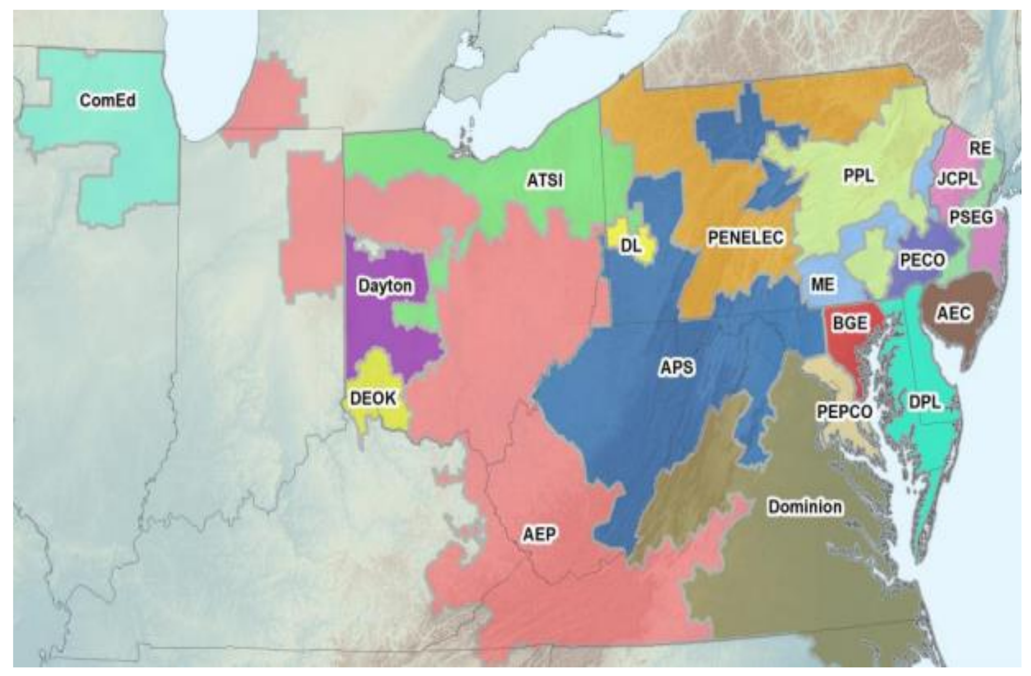

Fig. 2 PJM zones

A. Least absolute shrinkage and selection operator (LASSO) [1]

$$\varphi = 1 + \omega_1 x_1 + \omega_2 x_2 + \omega_3 x_1^2 + \omega_4 x_1 x_2 + \omega_5 x_2^3$$

x_1, x_2 are the features of the data set and y is the objective value. LASSO will find the best model for the data with this assumption through minimizing the residual sum of squares, and find a simpler model through limiting the summation of the absolute value of all ωs into a constant.

$$\min_{\omega_i} \frac{1}{2N} \sum_{k=1}^{N} (\varphi_k - y_k)^2$$

$$s.t. \sum_{i=1}^{5} |\omega_i| \le C$$

where N is the number of data.

Load	Alpha	R2 score	Related features
0	0.00122	0.8954	7, 12, 15, 26, 29, 35, 0
1	0.00122	0.90296	2, 6, 9, 17, 23, 27, 1
2	0.00031	0.89527	1, 4, 7, 17, 26, 27, 28, 29, 35, 2
3	0.00061	0.89708	5, 6, 8, 11, 26, 35, 3
4	0.00244	0.93125	7, 16, 4
5	0.00244	0.74046	3, 9, 12, 26, 5
6	0.00122	0.91518	1, 2, 3, 9, 6

Table I Related features of each load

B. Principal component analysis (PCA) [2]

PCA which is aiming to reveal the internal relationship of the data is a widespread method in reducing high-dimensional data to low-dimensional data keeping most key information. PCA projects the original high-dimensional data to a new coordinate system to convert the correlated variables into uncorrelated ones using orthogonal transformation.

In practical, those principal components remain enough information to do the subsequent analysis with much less computation burden.

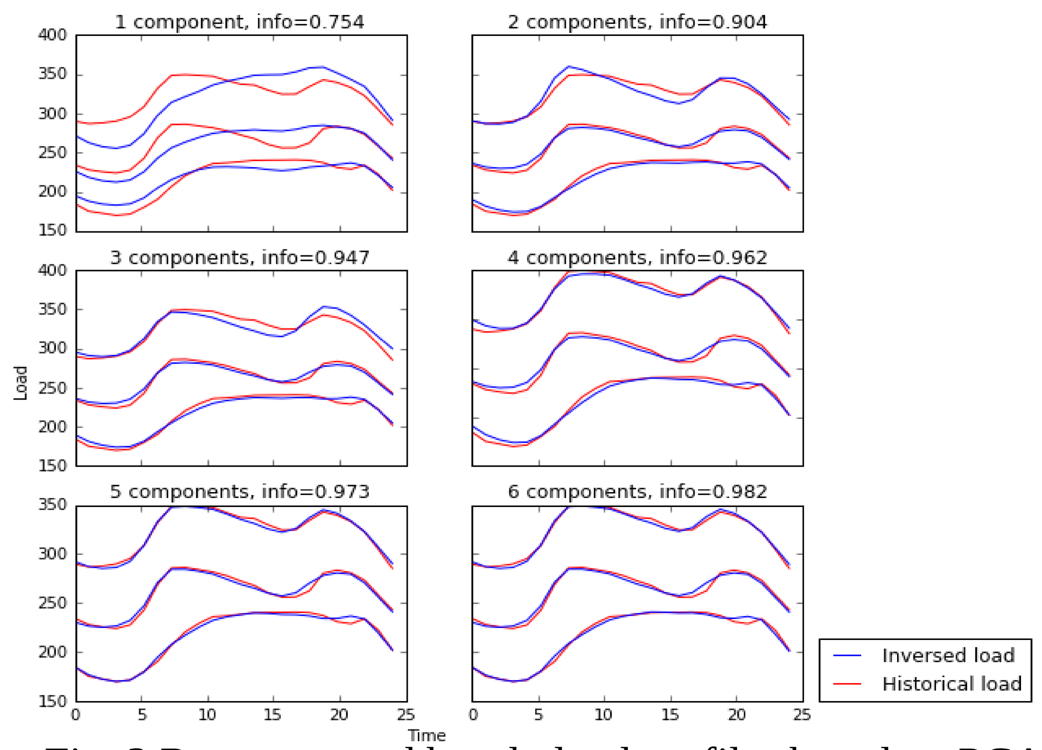

Fig. 3 Reconstructed hourly load profiles based on PCA

PCA is applied to the load of a 30-bus system, 504 (24 hours * 21 load) dimensions of data are gathered and decreased to 2 dimensions. Then, they are plotted monthly and with different colors to show the weekdays and weekends in Fig. 5 below. We can see clusters monthly and clear separations for weekday types in every month. In this way, more information can be extracted and we will use them to do load forecasting in the later on steps.

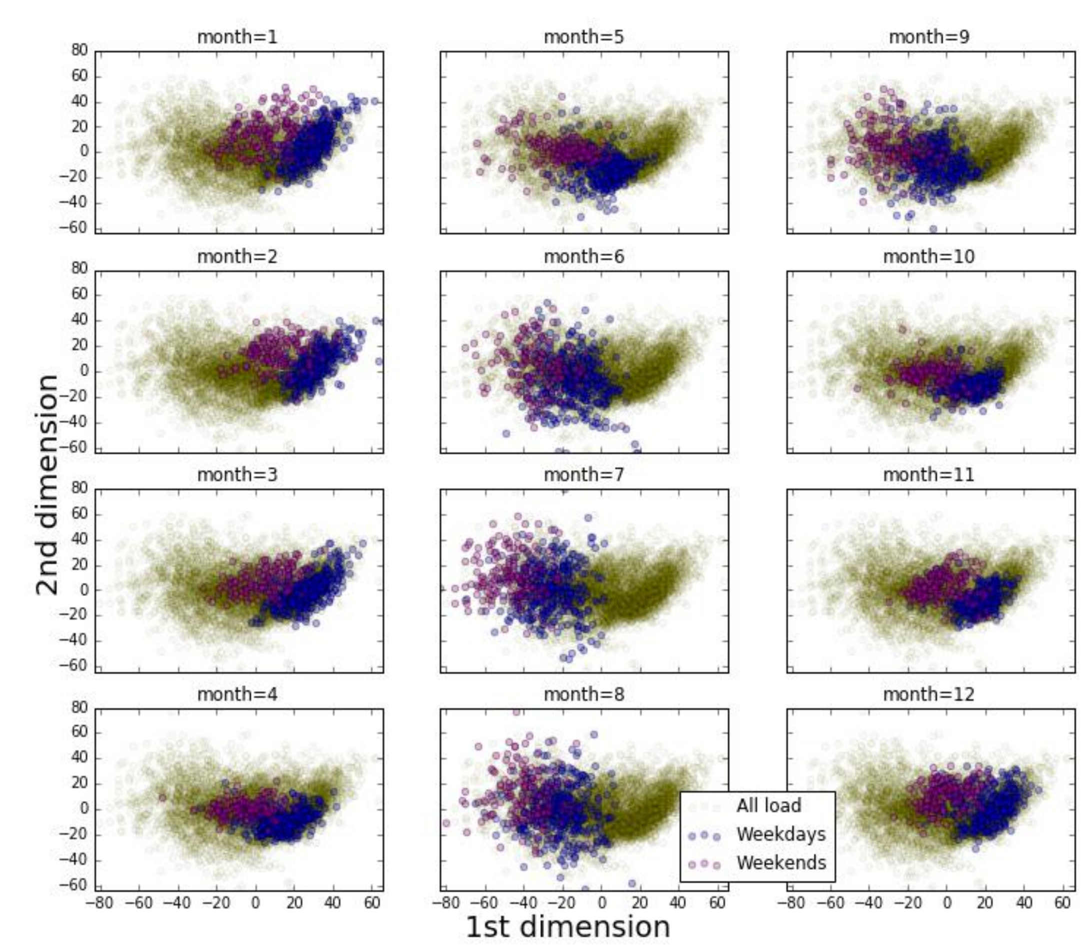

Fig. 4 Load data in 2-dimensional PCA space

C. Bayesian Ridge Regression (BRR) [3]

BRR is basically a linear model with a ridge part to penalize the complexity of the model and Bayesian treatment is involved to find the best parameter when adding the ridge part.

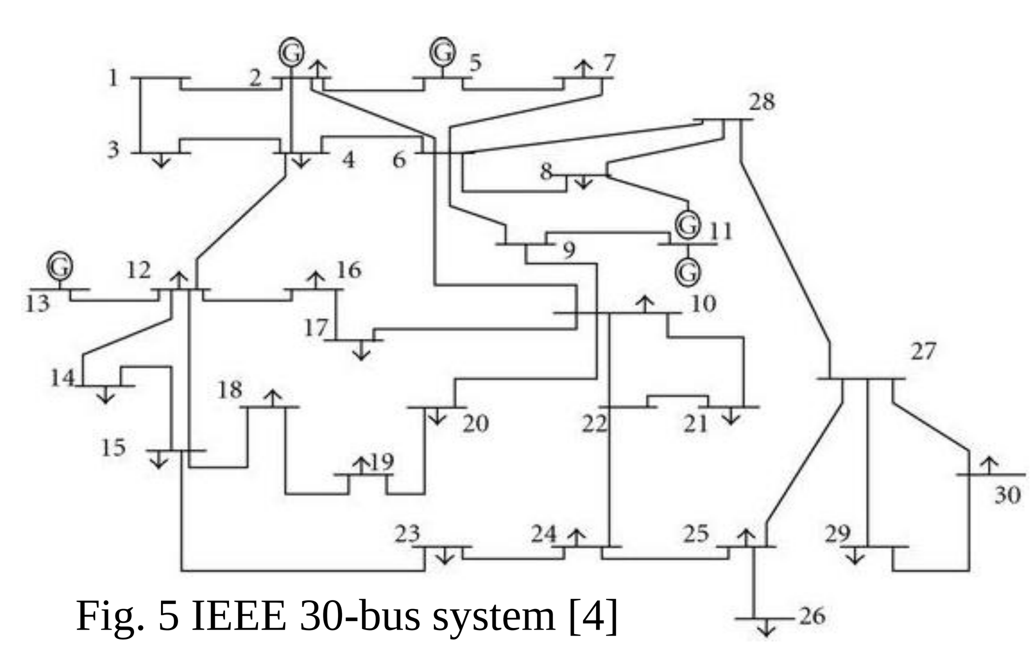

Fig. 5 IEEE 30-bus system [4]

III. CASE STUDIES

A 30-bus system will be used to demonstrate the effectiveness of the STNLF using LASSO, PCA and BRR. The shape of the 21 load may looks similar which is because of the nature of how people are using electricity, but the load levels are different which can be told by the y axis of each subplots.

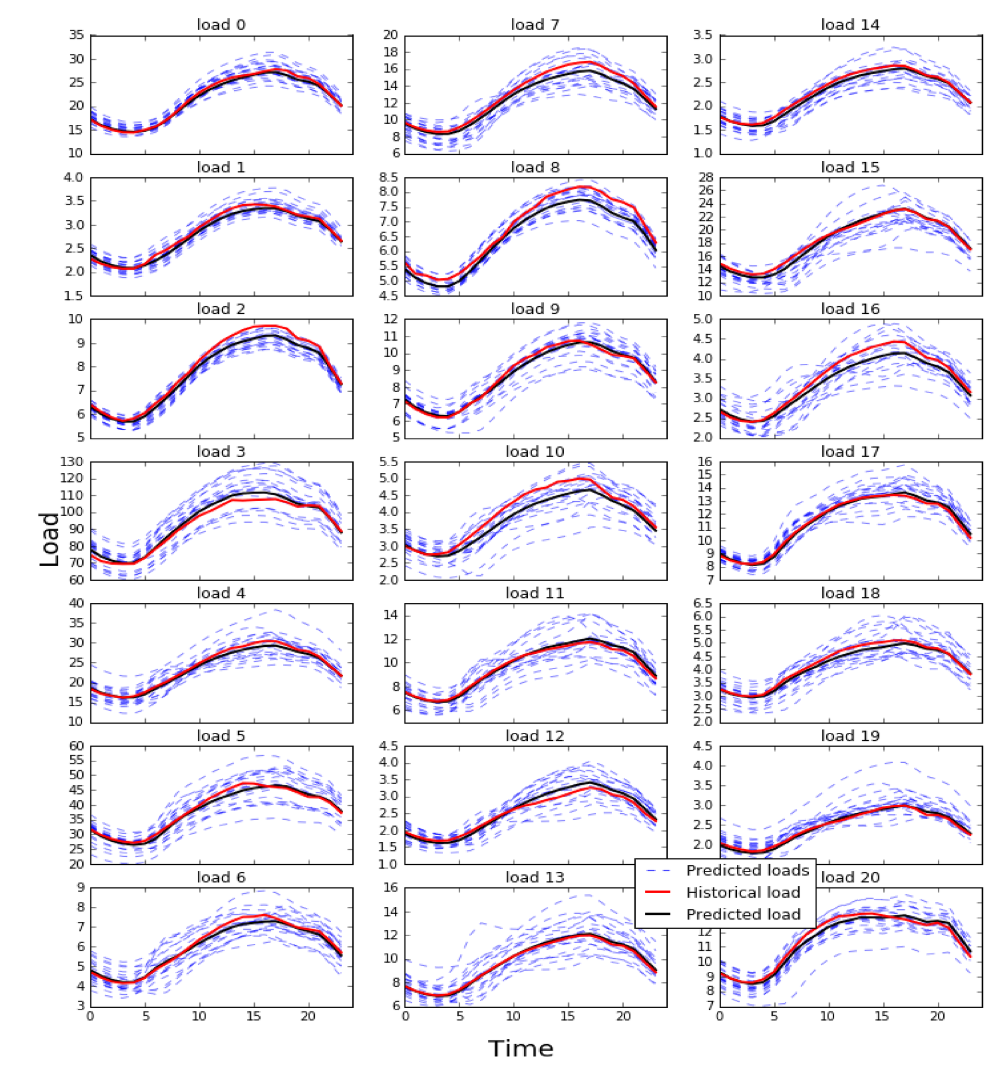

Fig. 6 Results for one day prediction

IV. CONCLUSION & FUTURE WORK

The simulation results show the effectiveness of the proposed methods for STNLF.

An immediate future work is to compare the proposed method with one or two general load forecasting methods, and apply the solution to support the next day Unit Commitment.

V. References

- [1] R. Tibshirani, "Regression Shrinkage and Selection via the Lasso," *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 58, pp. 267-288, 1996.
- [2] D. Lu, Z. Bao, and Z. Li, "Load Sampling for SCUC Based on Principal Component Analysis and Kernel Density Estimation," presented at the Power & Energy Society General Meeting, Boston, MA, 2016.
- [3] C. M. Bishop, *Pattern Recognition and Machine Learning (Information Science and Statistics)*: Springer-Verlag New York, Inc., 2006.
- [4] M. Shahidehpour and Y. Wang, "Appendix C: IEEE30 Bus System Data," in *Communication and Control in Electric Power Systems:Applications of Parallel and Distributed Processing*, ed: Wiley-IEEE Press, 2003, pp. 493-495.

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