Line Outage Detection and Localization via Synchrophasor Measurement

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\textbf{Abstract}—Since transmission lines are crucial links in the power system, one line outage event may bring about interruption or even cascading failure of the power system. If a quick and accurate line outage detection and localization can be achieved, the system operator can take necessary actions in time to mitigate the negative impact. Therefore, the objective of this paper is to study a method for line outage detection and localization via synchrophasor measurements. The density of deployed Phasor Measurement Units (PMUs) is increasing recently, which greatly improves the visibility of the power grid. Taking advantage of the high-resolution synchrophasor data, the proposed method utilizes frequency measurement for line outage detection and power change for localization. The procedure of the proposed method is given. Compared with conventional methods, it does not require the pre-knowledge on the system. Simulation study validates the effectiveness of the proposed method.

\textbf{Index Terms}—Detection and localization, Line outage, PMU, synchrophasor

\section{I. INTRODUCTION}

The detection and localization of transmission line outage in power system is of great significance for the system operators to take prompt action to avoid the widespread damage and maintain the reliability of power supply\textsuperscript{[1]}-\textsuperscript{[5]}. Most of current methods rely on angle data along with network susceptance matrix to calculate power injection change, which is a high computation burden and requires the information of system parameter \textsuperscript{[2]}, \textsuperscript{[6]}-\textsuperscript{[11]}. The method using PMU angle data and network susceptance was originally proposed in \textsuperscript{[2]} and pre- and post-outage power flow were calculated to match the measured event. Later, compressive sensing and global optimization techniques are proposed to improve the method in \textsuperscript{[7]} and \textsuperscript{[8]}. A general Bayesian criterion was employed to handle the uncertainty issue of PMU data in \textsuperscript{[9]}. Different new schema and frame are developed to deal with bad PMU measurements in \textsuperscript{[10]} and \textsuperscript{[11]}. However, the system parameter may not be available all the time due to strict security concerns.

With the rapid transformation from traditional power system into the smart grid, there are various types of novel applications involved into the system \textsuperscript{[12]}-\textsuperscript{[15]}. These smart grid applications are relying on the high quality synchronized data and advanced communication network infrastructure \textsuperscript{[16]}-\textsuperscript{[24]}, such as synchrophasor measurements, advanced metering infrastructure, and home energy management system. Nowadays, the density of synchrophasor is increasing dramatically to observe the dynamic behavior of the system following a contingency, which gives the unprecedented insights to the system \textsuperscript{[23]}-\textsuperscript{[28]}. For example, there are 114 and 238 PMUs installed at Jiangsu power grid, respectively. As shown in Fig. 1, the density of distributed PMU is significant high, which covers all 500kV transmission lines and parts of 220 kV transmission lines with the reporting rate 25 Hz. To utilize the PMU data and achieve wide area monitoring purpose, a PMU based situational awareness data analytics platform has been developed by Global Energy Interconnection Research Institute North America (GEIRINA) \textsuperscript{[29]}-\textsuperscript{[33]}. The PMU based platform collects synchrophasor measurements with massive channels in real time from Jiangsu power grids and processes large amount of data, which can be affected by latency from PMU device or communication network. The platform not only incorporates event detection application developed by GEIRINA, but also provide interface for event detection applications from third party. The density synchrophasor measurement brings the opportunity to detect the line outage location and locate the fault location without knowing the system parameters. The line outage detection approach introduced by \textsuperscript{[34]} was employed in the PMU based platform and the reported line outage locations have significant deviation from actual line outage location. Similar phenomenon was also founded in simulation cases in New England ISO (ISO-NE) and Tennessee Valley Authority (TVA) systems.

To address the issue mentioned above, this paper focuses on the method for line outage detection and localization via synchrophasor measurement. First, the line outage is detected via employing low pass filter and peak detector on synchronized frequency measurements. Once a line outage event is triggered, the location of the fault line will be pinpointed using power flow change. The requirement of computational effort for the whole process is not high thus outage location can be estimated in real time. The proposed method is straightforward and easy to implement. It also can be used for cross-checking line outage event via SCADA.

The rest of the paper is organized as follows. In Section II, the proposed line outage detection and localization method via

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synchrophasor measurement are given. In Section III, the characteristic of power flow change redistribution during line outage is explored via PSS/E simulation on models of ISO-NE and TVA systems. The simulation study on the ISO-NE model is conducted in Section IV. The conclusions and future work are drawn in Section V.

Fig. 1. Map of synchrophasor deployment in Jiangsu power grid [29]

II. LINE OUTAGE DETECTION AND LOCALIZATION

The proposed method for line outage detection and location estimation in the paper includes two steps: (1). Line outage event detection using frequency measurement; (2). Outage line localization using active power measurement.

The frequency measurements from deployed PMUs is used to monitor that if there is ongoing line outage event in the system. The principle of outage detection can be found in Ref. [34]-[36]. The frequency measurements are first fed into a moving median filter to remove random spikes and high-frequency noises. After that, a moving mean filter is used to extract the frequency trend as a reference. Then de-trended frequency data is subtracted frequency trend from filtered frequency measurements. Two thresholds are empirically set based on statistical analysis on historical data [34]. The event outage will be triggered using threshold evaluation. The event time can be determined via GPS timestamp on the measurements [37]-[40], which will be utilized further for event location estimation with active power measurements. When a line outage event happens, the active power flow will be redistributed partially since the power flow on the tripped line has to transfer the rest of the system abruptly, which provides useful information for line outage location estimation. The Power Transfer Distribution Factors (PTDFs) of line \( l \) respect to a power flow transaction \( \Delta w \) in a lossless model is defined as [41]-[44]:

\[
\varphi_l = \frac{\Delta l}{\Delta w}
\]  

(1)

where \( \Delta l \) is MW of power transfer between two location and \( \Delta w \) is the power transfer via branch \( l \) respect to the transaction. Then, for an outage at line \( m \), Line Outage Distribution Factor (LODF) is defined as the portion of pre-outage real power flow transfer to a line \( k \) [41], which can be represented as

\[
\varsigma_m = \frac{\Delta P_k}{P_m} = \frac{\varphi_k}{1 - \varphi_m}
\]  

(2)

where \( \Delta P_k \) is the power flow transfer changes at line \( k \) and \( P_m \) is the of pre-outage real power flow at line \( m \). According to the definition in Eq.(1) and (2), PTDFs and LODFs are less than 1.

Meanwhile, bus in pre-and post-outage condition must follow Gustav Kirchhoff’s Current Law (KCL). Defining the power flow change at terminal \( k \) is \( \Delta P_k \), the power flow change outage follows:

\[
\Delta P_{k_1} = \text{Sum}(\Delta P_j),
\]  

(3)

s.t., \( j \) ∈ branch connected to \( k_1 \)

where \( j \) is the indexes of the lines.

In an actual power system, the disturbance usually spread out from the source to the rest of the system. As a result, the bus with relatively large power flow changes might be closer to the location of the outage line, that is \( \Delta P_{k_1} > \Delta P_{k_2} \) when distance of \( k_1 \) to the outage location is smaller than \( j_1 \). Therefore, the bus of the outage line is likely to have the largest power change in the system.

Using the active power change from synchrophasor, the location of outage can be estimated. Specifically, once a line outage event is detected, noise in active power measurement is filtered by a median filter. With detected event timestamp, the active power change between pre-outage and the post-outage is calculated with the filtered active power measurements. By ranking the active power change on the monitored transmission lines, the location of the outage line can be determined with maximum value. The process of the line outage detection and localization method is presented in Fig. 2.

Fig. 2. Flowchart of line outage detection and localization

III. DISTRIBUTION OF POWER CHANGE IN TVA AND ISO-NE

This section investigates the characteristic of power flow change distribution caused by line outage via PSS/E simulation. Line outage events are simulated in both ISO-NE and TVA systems, respectively. ISO-NE system consists of 3447 buses and 2479 branches in 71,992 mile². The total generation is 18.1GW and total load is 21.8 GW in the system. There are 16 tie lines, which carry 3.7 GW power flow, connecting to the system. TVA system has 1920 buses and 1720 branches. There are 28.1 GW generation and 31.6 GW load within TVA system. The TVA system are connected with external system via 70 tie lines and total 3.5 GW energy are delivered by the tie lines. The
simplified system diagram of ISO-NE and TVA systems are showed in Fig. 3 and Fig. 4, respectively.

Fig. 3. ISO-NE model—transmission network map [45]

Fig. 4. Diagram for Tennessee Valley Authority [46]

TABLE I. ERROR ANALYSIS FOR LINE OUTAGE LOCATION ESTIMATION

| System | Case name | Terminal$_1$ (Lat, Lon) | Terminal$_2$ (Lat, Lon) | Power flow (MW) | Voltage level (kV) |
|--------|-----------|------------------------|------------------------|-----------------|-------------------|
| ISO-NE | Line$_1$  | 41.51,-72.56           | 41.29,-72.90           | 407.36          | 345               |
|        | Line$_2$  | 42.63,-71.05           | 42.70,-70.87           | 100.75          | 115               |
| TVA    | Line$_3$  | 35.10,-85.02           | 34.05,-85.08           | 856.78          | 500               |
|        | Line$_4$  | 37.78,-86.48           | 37.26,-86.98           | 246.72          | 161               |

For the purpose of a comprehensive study, 4 transmission lines in ISO-NE and TVA system are selected and tripped. The voltages levels of the outage line are from 115 kV to 500 kV. The terminal locations (latitude and longitude) of outage line and pre-outage real power flow on the lines are given in Table I. The locations of the disturbance and distribution of power flow changes caused by the line outage are shown from Fig. 5 to Fig. 6. It can be seen that the power flow changes at the terminals of the outage line have the highest value for the both cases. What is more, the power flow change closer the outage line generally has a larger value than the line far away from the event location.
IV. SIMULATION STUDY

To verify the effectiveness of the proposed method for line outage detection and localization, a simulation is conducted in ISO-NE which assumes that synchrophasor covers all 345 kV and part of (26%) 230 kV transmission lines. Line outages events are triggered in PSS/E to evaluate the performance of the events at different voltage levels. The parameters of the filter for line outage detection are selected based on [34], which are listed in Table II. The event detection module is implemented in C#, while location module is developed by MATLAB. The simulation tests are on a computer running a 64-bit Windows 10, with a 3.60 GHz Intel I7-7700U CPU and 16 GB memory.

| Parameters                  | Values   |
|-----------------------------|----------|
| Median filter window        | 7 points |
| Mean filter size            | 31 points|
| Detection window            | 20 points|
| First peak threshold        | 0.0045 Hz|
| Second peak threshold       | 0.0025 Hz|

The line outage events can be successfully detected, and event time can be accurately recorded for all simulation cases. The location estimation of the events is further analyzed. The information of the line outage location and estimation error are in Table III. As shown in the Table III, the proposed method is able to identify the outage line location precisely, when the outage lines are monitored by synchrophasor. For the outage lines without synchrophasor monitoring (115 kV), the estimated location is close to actual outage line terminals. For the cases with a large error in 115 kV case, the actual outage lines are far away from PMU locations and the reported PMU is the closest location to the actual outage line terminals.

| Voltage level | Monitored by PMU | Cases numbers | Max error (Mile) | Average error (Mile) |
|---------------|-------------------|---------------|------------------|----------------------|
| 345 kV        | Y                 | 37            | 0                | 0                    |
| 230 kV        | Y                 | 20            | 0                | 0                    |
| 230 kV        | N                 | 8             | 13.72            | 6.32                 |
| 115 kV        | N                 | 30            | 82.49            | 10.42                |

TABLE III. RESULT OF LINE OUTAGE LOCATION ESTIMATION

| Case name | Voltage level | Monitored by PMU | Power flow (MW) | Power change (mile) | Max freq. (mile) |
|-----------|---------------|-------------------|-----------------|---------------------|------------------|
| 1         | 345 kV        | Y                 | 725.17          | 0                   | 93               |
| 2         | 230 kV        | Y                 | 224.43          | 0                   | 123              |
| 3         | 230 kV        | N                 | 285.65          | 9.366               | 126              |
| 4         | 115 kV        | N                 | 100.45          | 0                   | 18               |

TABLE IV. PERFORMANCE COMPARISON FOR LOCATION ESTIMATION
For the purpose of comparison, the locations of four line outage cases from 115 kV and 345 kV are estimated by the proposed methods and the traditional methods using the maximum frequency magnitude change in Ref.[34] and [47]. The estimation errors for each case are given in Table IV. The estimation locations and actual locations by proposed methods and the traditional methods are plotted in Fig. 7 to Fig. 10. As shown in these figures, distances between the estimated locations by proposed methods and the actual location of outage line are small while the estimated location by methods using frequency changes has significant deviations from actual outage locations.

V. CONCLUSION AND FUTURE WORKS
Awareness of line outage event and its location is critical to prevent cascading outages in today's modern power system. This paper presents a fast line outage detection and localization method utilizing synchrophasor measurements. The line outage is first detected via a peak detector on synchronized frequency measurements, and location of the fault line is directly estimated via active power flow change. The proposed is straightforward and does not need the pre-knowledge on system topology and parameters. The feature of active power change distribution caused by line outage is explored in both TVA and ISO-NE system. A comprehensive simulation study in ISO-NE shows the method can precisely identify the outage line with reasonable accuracy. It can works as an effective tool for real-time line outage detection and localization.

Simulation results manifest that the proposed approach is promising for line outage detection and localization in large-scale power system. The performances of the proposed approach have not been validated with line outage events from real power grid. Additionally, the approach has not been fully tested for real-time implementation. Following are some future works for further development:

1) Validate the proposed approached with confirmed line outage event from power grid utilities.
2) Test the robustness of the approach with synchrophasor measurements with low quality data.
3) Develop interface with available PMU data platform and evaluate the performance of this approach with real synchrophasor measurements.

VI. REFERENCES

[1] J. Chen, Y. Zhao, A. Goldsmith, and H. V. Poor, "Line outage detection in power transmission networks via message passing algorithms," Signals, Systems and Computers, 2014 48th Asilomar Conference, 2014, pp. 350-354.
[2] J. E. Tate and T. J. Overbye, "Line Outage Detection Using Phasor Angle Measurements," IEEE Trans. Power Systems, vol. 23, no. 4, pp. 1644-1652, Nov. 2008.
[3] K. Dave, N. Mohan, X. Deng, R. Gorur and R. Olsen, "Analyzing techniques for increasing power transfer in the electric grid," 2012 North American Power Symposium (NAPS), Champaign, IL, 2012, pp. 1-6.
[4] X. Deng, "Exploring Six-Phase Transmission Lines for Increasing Power Transfer With Limited Right of Way " M.Sc. Thesis, Arizona State University, 2012
[5] X. Deng, Y. Chen and Ying Li, "Study on the CIM based data integration platform," ISGT 2011, Hilton Anaheim, CA, 2011, pp. 1-5.
[6] J. Zhao, J. Tan, L. Wu, L. Zhan, W. Yao, Y. Liu, J. Gracia, P. Ewing, "PMU error impact on measurement-based applications", 2017 IEEE PES General Meeting, Chicago, IL, 2017.
[7] J. H. Zhu and G. B. Giannakis, “Sparse overcomplete representations for efficient identification of power line outages,” IEEE Trans. Power Syst., vol. 27, no. 4, pp. 2215–2224, Nov. 2012.
[8] J.-C. Chen, W.-T. Li, C.-K. Wen, J.-H. Teng, and P. Ting, "Efficient identification method for power line outages in the smart power grid.,” IEEE Trans. Power Syst., vol. 29, no. 4, pp. 1788–1800, Jul. 2014.
[9] C. Chen, J. Wang and H. Zhu, "Effects of Phasor Measurement Uncertainty on Power Line Outage Detection," IEEE Journal of Selected Topics in Signal Processing, vol. 8, no. 6, pp. 1127-1139, Dec. 2014.
[10] A., Mehebub, M. Bissawanjan, S., Siddhartha, "A New Approach of Multiple Line Outage Identification Using Phasor Measurement Unit (PMU) with Bad Data," 2018 International Conference on Current Trends towards Converging Technologies.
[11] W. Li, C. Wen, J. Chen, K. Wong, J. Teng and C. Yuen, "Location Identification of Power Line Outages Using PMU Measurements With Bad Data," IEEE Transactions on Power Systems, vol. 31, no. 5, pp. 3624-3635, Sept. 2016.
[12] D. Bian, M. Pipattanasomporn and S. Rahman, "A Human Expert-Based Approach to Electrical Peak Demand Management," in IEEE Transactions on Power Delivery, vol. 30, no. 3, pp. 1127-1139, June 2015.
[13] Z. Liang, D. Bian, X. Zhang, D. Shi, R. Diao, Z. Wang, "Optimal energy management for commercial buildings considering comprehensive comfort levels in a retail electricity market," Applied Energy, Volume 236, 2019, pp. 916-926.
[14] Y. Yan, D. Shi, D. Bian, B. Huang, Z. Yi and Z. Wang, "Small-signal Stability Analysis and Performance Evaluation of Microgrids under Distributed Control,” in IEEE Transactions on Smart Grid, 2018, pp. 1-1.
[15] Z. Liang, D. Bian, D. Su, R. Diao, D. Shi, Z. Wang, and W. Su, "Adaptive Robust Energy Management Strategy for Campus-Based Commercial Buildings Considering Comprehensive Comfort Levels," in IEEE PES General Meeting (GM), Atlanta, GA, 2019.
[16] D. Shi, X. Chen, Z. Wang, X. Zhang, Z. Yu, X. Wang, D. Bian, “A Distributed Cooperative Control Framework for Synchronized
Reconnection of a Multi-Bus Microgrid," in IEEE Transactions on Smart Grid, vol. 9, no. 6, pp. 6646-6655, Nov. 2018.

[17] D. Bian, M. Kuzlu, M. Pipattanasomporn, S. Rahman and Y. Wu, "Real-time co-simulation platform using OPAL-RT and OPNET for analyzing smart grid performance," 2015 IEEE Power & Energy Society General Meeting, Denver, CO, 2015, pp. 1-5.

[18] D. Bian, M. Kuzlu, M. Pipattanasomporn, S. Rahman, D. Shi, "Performance Evaluation of Communication Technologies and Network Structure for Smart Grid Applications," IET Communications, accepted, 2019.

[19] D. Bian, M. Kuzlu, M. Pipattanasomporn, S. Rahman, "Analysis of Communication Schemes for Advanced Metering Infrastructure (AMI)," in IEEE PES General Meeting, National Harbor, MD, 2014.

[20] D. Bian, M. Kuzlu, M. Pipattanasomporn, S. Rahman, "Assessment of Communication Technologies for a Home Energy Management System," in IEEE PES Innovative Smart Grid Technologies Conference (ISGT), Washington, D.C., 2014.

[21] D. Bian, "A Novel Space-Time System Based on Turbo Channel Estimation Method," in International Conference on Wireless Communications, Networking and Mobile Computing, Dalian, China, 2008.

[22] D. Bian, D. Shi, M. Pipattanasomporn, M. Kuzlu and S. Rahman, "Mitigating the Impact of Renewable Variability with Demand-Side Resources Considering Communication and Cyber Security Limitations," in IEEE Access, vol. 7, pp. 1379-1389, 2019.

[23] D. Bian, H. Latchman, "High Speed Powerline Communications: State of the Art and Beyond," in International Multi-Conference on Complexity, Informatics and Cybernetics (IMCIC), Tampa, FL, 2011.

[24] Y. Meng, Z. Yu, D. Shi, D. Bian and Z. Wang, "Forced Oscillation Source Location via Multivariate Time Series Classification," 2018 IEEE/PES Transmission and Distribution Conference and Exposition (T&D), Denver, CO, 2018, pp. 1-5.

[25] Y. Liu et al., "A Distribution Level Wide Area Monitoring System for the Electric Power Grid—FNET/GridEye," in IEEE Access, vol. 5, pp. 2329-2338, 2017.

[26] C. Li, W. Zhou, and Sh. Yuan, "Iris recognition based on a novel variation of local binary pattern." The Visual Computer 31.10 (2015): 1419-1429.

[27] J. Zhang, L. Zhang, Z. Ren, Y. Chen, S. Huang, “Coupled analysis of energy flow in a multiple energy system”, 2017 IEEE Conference on Energy Internet and Energy System Integration (EI2), 26-28 Nov 2017.

[28] H. Liu, L. Zhu, Z. Pan, and et al. "ARMAX-based Transfer Function Model Identification Using Wide-area Measurement for Adaptive and Coordinated Damping Control", IEEE Trans. Smart Grid, 2017, 1105-1115.

[29] D. Bian, Z. Yu, D. Shi, R. Diao, Z. Wang, "A Robust Low-Frequency Oscillation Detection and Analysis (LFODA) System with Innovative Ensemble Filtering for Real-time Grid Operation," CSEE Journal of Power and Energy Systems, accepted, 2019.

[30] X. Deng, G. He, Y. Chen, W. Zhang, “CIM Leaderin Based on Java Refactoring Mechanism in AEMS of Shanghai Power Grid,” Automation of Electric Power System, 2007, vol.31, no.18, pp. 21-24

[31] Y. Liu et al., "Recent developments of FNET/GridEye — A situational awareness tool for smart grid," in CSEE Journal of Power and Energy Systems, vol. 2, no. 3, pp. 19-27, Sept. 2016.

[32] H. Liu, J. Guo, W. Yu, T. Xia, R. Sun, M. Gardner, L. Zhu, Y. Liu. "The Design and Implementation of the Enterprise Level Data Platform and Big Data Driven Applications and Analytics", 2016 IEEE PES Transmission & Distribution Conference & Exposition, 2015.

[33] X. Lu, D. Shi and et al., "PMU assisted power system parameter calibration at Jiangsu electric power company," IEEE Power & Energy Society General Meeting, Chicago, IL, 2017, pp. 1-5.

[34] D. Zhou, Y. Liu and J. Dong, "Frequency-based real-time line trip detection and alarm trigger development," IEEE PES General Meeting, National Harbor, MD, 2014, pp. 1-5.

[35] C. Li, Z. Wang and H. Qi, "Fast-Converging Conditional Generative Adversarial Networks for Image Synthesis," 2018 25th IEEE International Conference on Image Processing (ICIP), Athens, 2018, pp. 2132-2136.

[36] J. Zhao, L. Zhan, Y. Liu, H. Qi, J. R. Garcia, P. D. Ewing, "Measurement accuracy limitation analysis on synchrophasors", 2015 IEEE PES General Meeting, Denver, CO, 2015.

[37] W. Yao, Y. Liu, D. Zhou, Z. Pan, J. Zhao, M. Till, L. Zhu, L. Zhan, Q. Tang and Y. Liu, Impact of GPS Signal Loss and Its Mitigation in Power System Synchronized Measurement Devices, IEEE Transactions on Smart Grid, vol. 9, no. 2, pp. 1141-1149, March 2018.

[38] W. Yao, D. Zhou, L. Zhan, Y. Liu, Y Cui, S. You and Y. Liu, GPS signal loss in the wide area monitoring system: Prevalence, impact, and solution, Electric Power Systems Research, vol.147, pp. 254-262, 2017

[39] X. Deng, H. Li, W. Yu, W. Wang, Y. Liu, " Frequency Observations and Statistic Analysis of Worldwide Man Power Grids Using FNET/GridEye, " 2019 IEEE Power & Energy Society General Meeting, Atlanta, GA.

[40] J. Zhao, S. You, H. Yin, J. Tan, Y. Liu, "Data quality analysis and solutions for distribution-level PMUs", 2019 IEEE PES General Meeting, Atlanta, GA, 2019.

[41] A. Wood and B. Wollenberg, Power Generation Operation and Control, 2nd ed. New York: Wiley, 1996, p. 422.

[42] H. Liu, J. Guo, W. Yu, T. Xia, R. Sun, M. Gardner, L. Zhu, Y. Liu. "The Design and Implementation of the Enterprise Level Data Platform and Big Data Driven Applications and Analytics", 2016 IEEE PES Transmission & Distribution Conference & Exposition, 2015.

[43] J.Z. Wang, D.Wang et al, "Deep reinforcement learning of cell movement in the early stage of C. elegans embryogenesis," Bioinformatics, 2018, 1 p.9.

[44] T. Guler, G. Gross and M. Liu, "Generalized Line Outage Distribution Factors," in IEEE Transactions on Power Systems, vol. 22, no. 2, pp. 879-881, May 2007.

[45] ISO-NE model—transmission network map, available at: https://www.nrel.gov/docs/fy14osti/61824.pdf

[46] Tennessee Valley Authority. electric infrastructure, available at: https://www.eia.gov/todayinenergy/detail.php?id=11151

[47] Y. Song, W. Wang, Z. Zhang, H. Qi and Y. Liu, "Multiple Event Detection and Recognition for Large-Scale Power Systems Through Cluster-Based Sparse Coding," IEEE Trans. Power Systems, vol. 32, no. 6, pp. 4199-4210, Nov. 2017.