Advanced Data Analytics for Improving the Situational Awareness of the Peak Reliability System

Cooperative Research and Development Final Report

CRADA Number: CRD-17-00706

Technical Contacts:
NREL: Venkat Krishnan and Yingchen Zhang
Peak Reliability (Partner): Jason Ausmus

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Office of Energy Efficiency & Renewable Energy
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Contract No. DE-AC36-08GO28308

Technical Report
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NOTICE

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Cooperative Research and Development Final Report

Report Date: September 23, 2020

In accordance with requirements set forth in the terms of the CRADA agreement, this document is the final CRADA report, including a list of subject inventions, to be forwarded to the DOE Office of Scientific and Technical Information as part of the commitment to the public to demonstrate results of federally funded research.

Parties to the Agreement: Peak Reliability

CRADA Number: CRD-17-00706

CRADA Title: Advanced Data Analytics for Improving the Situational Awareness of the Peak Reliability System

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Sponsoring DOE Program Office(s):

Office of Energy Efficiency and Renewable Energy, Solar Energy Technologies Office (SETO)

Joint Work Statement Funding Table showing DOE commitment:

No NREL Shared Resources

Estimated Costs	NREL Shared Resources a/k/a Government In-Kind
Year 1	$.00
TOTALS	$.00

Executive Summary of CRADA Work:

NREL will collaborate with Peak to develop advanced data analytics methods to improve the situational awareness of its RC area by utilizing measurement data. The main objective is to develop accurate load forecasting methods to predict system loads at different temporal scales.

Summary of Research Results:

This work sought to address Peak Reliability's ("Peak") needs for improving the situational awareness of its Reliability Coordinator (RC) area by extracting specific data useful for real-time system operations, from the mass amount of data Peak has by using advanced data analytics methods. The team developed improved load forecasting algorithms taking into consideration different high resolution nodal level load data from the Peak RC. Traditionally, day-ahead load forecasting are done at the aggregate regional level; and nodal loads are estimated with constant proportions or load shapes. But looking at the nodal data reveals the fact that every node has varying characteristics and constant proportional split of regional load into nodal loads falls short of realistic estimates. Therefore, the team employed advanced machine learning algorithms to utilize the high resolution nodal level load data from RC, and used them to cluster loads into appropriate categories, and developed a scalable load forecasting algorithm that is better than the business as usual practice. The improved performance was validated using the actual load data of RC area from SCADA and PMU data.

CRADA Task 1: Data preparation and transfer

(Task 1.1) The figures Fig. 1 and Fig. 2 below summarizes the Peak RC data that was used in the study. (System model date including load data.) (Task 1.2) Fig. 1 also summarizes the cleaning and preparation process adopted to clean the raw measurement (PMU and SCADA) and state estimation (SE) data for more than 500 buses. The 5-min data were resampled and averaged to hourly profiles, and 200 buses that had continuous data for 3 years (training data for the machine learning LM models) were selected. Fig. 2 shows the time series data for 3 years at hourly intervals.

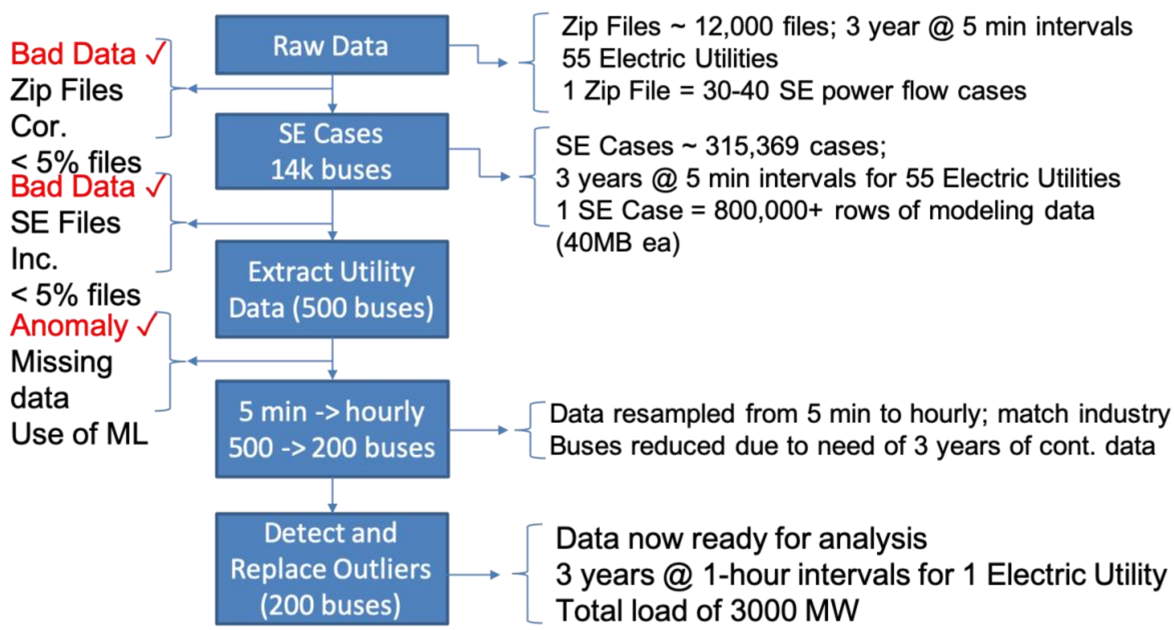

Fig. 1 Overview of Peak RC data and the cleaning process

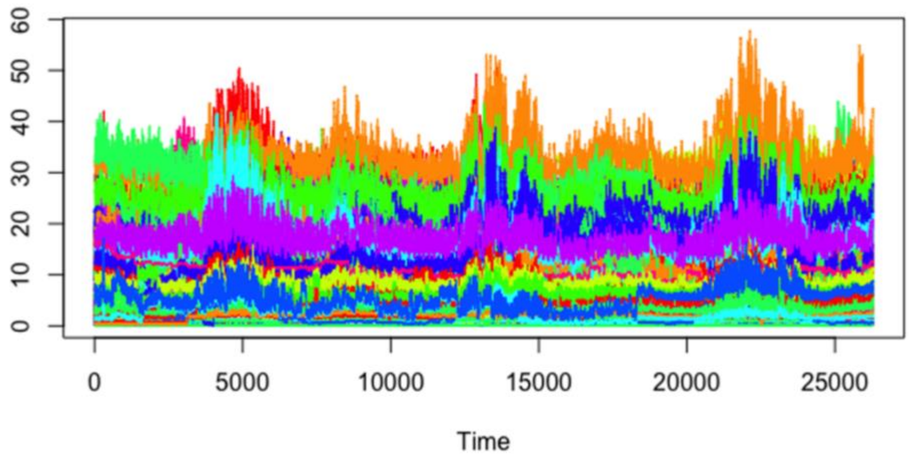

Fig. 2 Time series data for about 200 nodes/buses from 1 utility

CRADA Task 2: Develop accurate load forecasting methods:

The Fig. 3 below summarizes the forecasting method, that begins with clustering 200 different buses into 12 representative load profiles. This ensure we can develop a scalable forecasting techniques, where all the 200 time series profiles can be categorized into major 10-12 categories. The number "12" in this study was estimated by performing several different k-means clusters and identifying the appropriate number of clusters that: 1) maximizes the inter-cluster centroid distance between two different clusters, and 2) minimizes the intra-cluster distances between all the points from the cluster centroid. More information about the clustering method will be found in the publication [1] below, and also attached as addendum to this report.

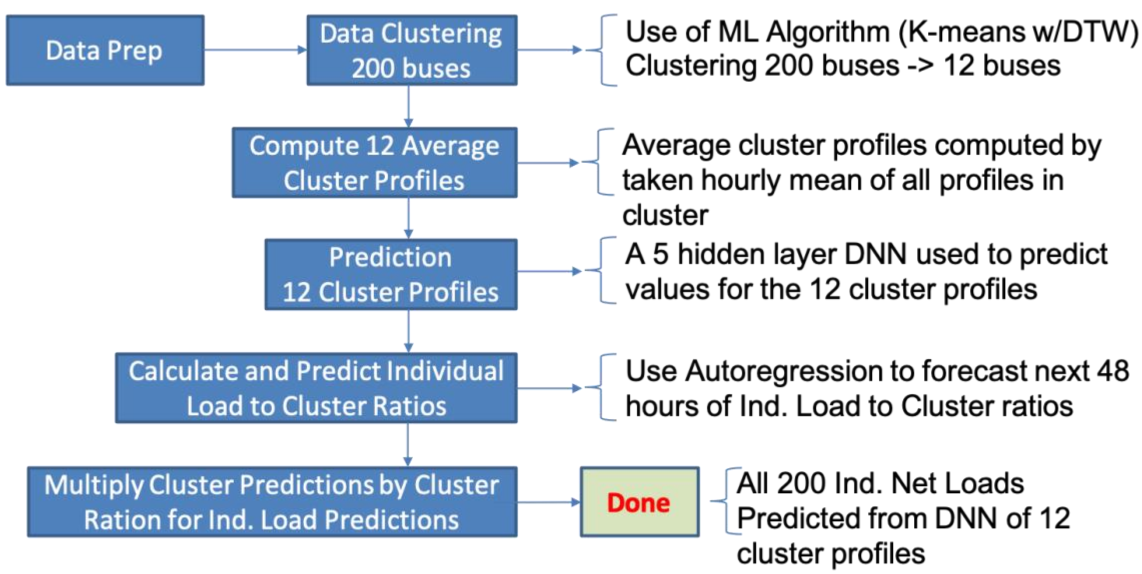

Fig. 3 Summary of the scalable load forecasting method that uses clustering and machine learning methods

Then, for each cluster, load forecasting is performed using deep neural networks (DNN). Multi-layer DNN is used to improve the accuracy, as seen in Fig. 4 that shows the results of forecasting for one of the clusters (cluster 7) single. The single layer NN result is compared with the 2-layers and 3-layeres DNN. Simple techniques such as multiple linear regression also needed further improvements. This is because load forecasting is a non-linear problem that depend upon multiple factors such as weather variables (temperature, humidity, solar irradiation, wind speed), economic conditions, and time of the day (hour, day, weekday, events, holiday, etc.). Therefore, as seen from Fig. 4, multiple layer DNN that has multiple hidden layers were used, so that the data were automatically separated by the NN through various layers, and a complicated nonlinear relationship between the inputs and output is modeled to improve the prediction. This result therefore demonstrates the use of ML techniques to improve the load forecasting. It is to be noted that in this work nodal load data from peak RC has been used, there utilizing a large set of realistic data. The methods and results of this work has also been summarized in the manuscript [2] below that is currently under review by a peer-reviewed journal.

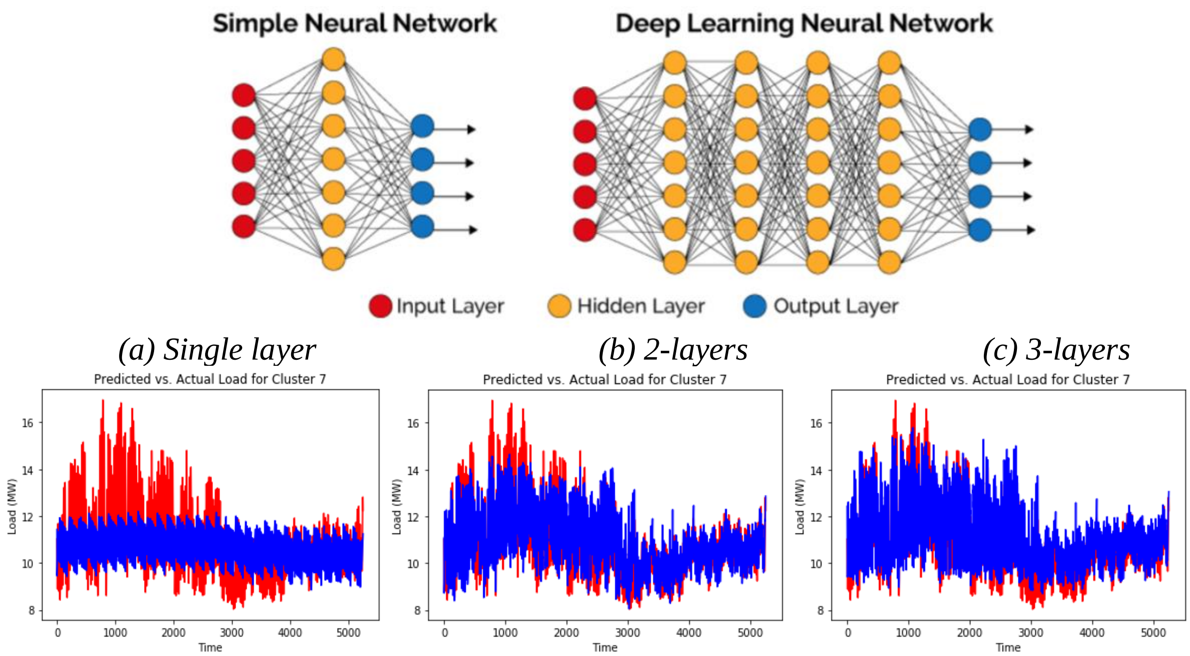

Fig. 4 Single layer vs. multi-layer DNN for load forecasting of one of the clusters

Publications or Manuscripts:

[1] J. R. Ausmus, P. K. P. Sen, T. Wu, U. Adhikari, Y. Zhang and V. Krishnan, "Improving the Accuracy of Clustering Electric Utility Net Load Data using Dynamic Time Warping," 2020 IEEE/PES Transmission and Distribution Conference and Exposition (T&D), Chicago, IL, 2020, pp. 1-5, doi: 10.1109/TD39804.2020.9299915.

[2] J. Ausmus, Y. Zhang, V. Krishnan, T. Wu, and P. Sen, "Efficient Forecasting of Net Electric Load Data using DNN and Clustering Algorithms at the Nodal Level," *at the time this CRADA report was released, this article is under review by Journal of Modern Power Systems and Clean Energy. In the event a journal does not accept the article, the researchers may publish the article as an NREL publication.*

Additional References:

In lieu of the delayed references above, the papers are out of this PhD dissertation, where this work and results have been documented:
https://mountainscholar.org/bitstream/handle/11124/174168/Ausmus_mines_0052E_11943.pdf?sequence=1&isAllowed=y
https://mountainscholar.org/handle/11124/174168

Subject Inventions Listing:

None

Record of Invention (ROI) #:

None