Big IoT data mining for real-time energy disaggregation in buildings (extended abstract)

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Abstract

In the smart grid context, the identification and prediction of building energy flexibility is a challenging open question. In this paper, we propose a hybrid approach to address this problem. It combines sparse smart meters with deep learning methods, e.g. Factored Four-Way Conditional Restricted Boltzmann Machines (FFW-CRBMs), to accurately predict and identify the energy flexibility of buildings unequipped with smart meters, starting from their aggregated energy values. The proposed approach was validated on a real database, namely the Reference Energy Disaggregation Dataset.

1. Introduction

Unprecedented high volumes of data and information are available in the smart grid context, with the upward growth of the smart metering infrastructure. This recently developed network enables two-way communication between smart grid and individual energy consumers (i.e., the customers), with emerging needs to monitor, predict, schedule, learn and make decisions regarding local energy consumption and production, all in real-time. One possible way to detect building energy flexibility in real-time is by performing energy disaggregation (Zeifman & Roth, 2011). In this paper (Mocanu et al., 2016), we propose an unified framework which incorporates two novel deep learning models, namely Factored Four-Way Conditional Restricted Boltzmann Machines (FFW-CRBM) (Mocanu et al., 2015) and Disjunctive Factored Four-Way Conditional Restricted Boltzmann Machines (DFFW-CRBM) (Mocanu et al., 2017), to perform energy disaggregation, flexibility identification and flexibility prediction simultaneously.

2. The proposed method

Recently, it has been proven that it is possible in an unified framework to perform both, classification and prediction, by using deep learning techniques, such as in (Mocanu et al., 2014; Mocanu et al., 2015; Mocanu et al., 2017). Consequently, in the context of flexibility detection and prediction, we explore the generalization capabilities of Factored Four-Way Conditional Restricted Boltzmann Machines (FFW-CRBM) (Mocanu et al., 2015) and Disjunctive Factored Four-Way Conditional Restricted Boltzmann Machines (DFFW-CRBM) (Mocanu et al., 2017). Both models, FFW-CRBM and DFFW-CRBM, have shown to be successful on outperforming state-of-the-art techniques in both, classification (e.g. Support Vector Machines) and prediction (e.g. Conditional Restricted Boltzmann Machines), on time series classification and prediction in the context of human activity recognition, 3D trajectories estimation and so on. In Figure 1 a high level schematic overview of FFW-CRBM and DFFW-CRBM functionalities is depicted, while for a comprehensive discussion on their mathematical details the interested reader is referred to (Mocanu et al., 2015; Mocanu et al., 2017). The full methodology to perform energy disaggregation can be found in (Mocanu et al., 2016).

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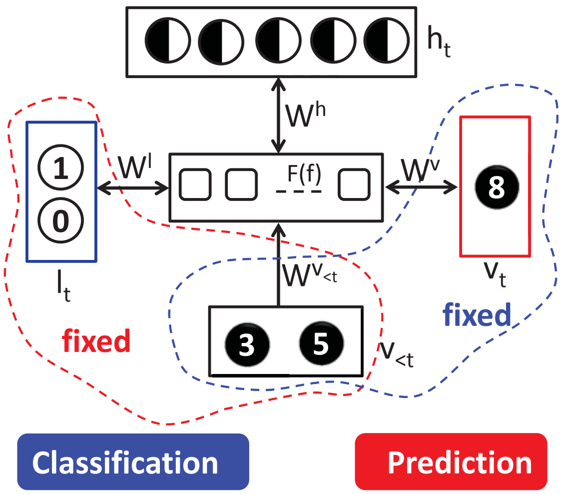

Figure 1. Classification and prediction schemes for FFW-CRBMs (DFFW-CRBM function in a similar manner). To perform classification the value of each neuron from the dotted blue area has to be fixed (i.e. present and history layers) and to let the model to infer the values of the label neurons. To perform prediction the value of each neuron from the dotted red area has to be fixed (i.e. label and history layers) and to let the model to infer the values of the present neurons.

We assessed our proposed framework on the The Reference Energy Disaggregation Dataset (REDD) dataset (Kolter & Johnson, 2011). The results presented in Table 1 and 2 show that both models performed very well obtaining a minimum prediction error on the power consumption of 1.85% and a maximum error of 9.36%, while for the time-of-use prediction the minimum error reached was 1.77% in the case of the electric heater and the maximum error obtained was 8.79% for the refrigerator.

3. Conclusion

In this paper, we proposed a novel IoT framework to perform simultaneously and in real-time flexibility identification and prediction, by making use of Factored Four Way Conditional Restricted Boltzmann Machines and their Disjunctive version. The experimental validation performed on a real-world database shows that both models perform very well, reaching a similar performance with state-of-the-art models on flexibility identification, while having the advantage of being capable to perform also flexibility prediction.

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Table 1. Results showing accuracy [%] and balanced accuracy [%] for FFW-CRBM and DFFW-CRBM, when classifying an appliance versus all data.

Appliance	Method	Accuracy [%]	Balanced accuracy [%]
refrigerator	FFW-CRBM	86.23	90.05
	DFFW-CRBM	83.10	91.27
dishwasher	FFW-CRBM	97.42	80.21
	DFFW-CRBM	97.26	87.06
washer dryer	FFW-CRBM	98.83	99.03
	DFFW-CRBM	99.06	92.16
electric heater	FFW-CRBM	99.10	90.58
	DFFW-CRBM	99.03	92.05

Table 2. Results showing the NRMSE [%] obtained to estimate the electrical demand and the time-of-use for four building electrical sub-systems using FFW-CRBM and DFFW-CRBM.

Appliance	Method	Power NRMSE [%]	Time-of-use NRMSE [%]
refrigerator	FFW-CRBM	9.36	8.79
	DFFW-CRBM	9.27	8.71
dishwasher	FFW-CRBM	5.49	5.89
	DFFW-CRBM	5.41	5.87
washer dryer	FFW-CRBM	2.70	2.43
	DFFW-CRBM	2.59	2.44
electric heater	FFW-CRBM	1.86	1.78
	DFFW-CRBM	1.85	1.77

References

Kolter, J. Z., & Johnson, M. J. (2011). REDD: A Public Data Set for Energy Disaggregation Research. *SustKDD Workshop on Data Mining Applications in Sustainability*. San Diego, California, USA.

Mocanu, D. C., Ammar, H. B., Lowet, D., Driessens, K., Liotta, A., Weiss, G., & Tuyls, K. (2015). Factored four way conditional restricted boltzmann machines for activity recognition. *Pattern Recognition Letters*, *66*, 100 – 108.

Mocanu, D. C., Ammar, H. B., Puig, L., Eaton, E., & Liotta, A. (2017). Estimating 3d trajectories from 2d projections via disjunctive factored four-way conditional restricted boltzmann machines. *Pattern Recognition*.

Mocanu, D. C., Mocanu, E., Nguyen, P. H., Gibescu, M., & Liotta, A. (2016). Big iot data mining for real-time energy disaggregation in buildings. *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* (pp. 003765–003769).

Mocanu, E., Mocanu, D. C., Ammar, H. B., Zivkovic, Z., Liotta, A., & Smirnov, E. (2014). Inexpensive user tracking using boltzmann machines. *2014 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* (pp. 1–6).

Zeifman, M., & Roth, K. (2011). Nonintrusive appliance load monitoring: Review and outlook. *IEEE Transactions on Consumer Electronics*, *57*, 76–84.