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Editorial

Special Issue: "Energy Data Analytics for Smart Meter Data"

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Smart electricity meters are a cornerstone for the realization of next-generation electrical power grids. In addition to measuring electrical consumption data at much greater temporal and amplitude resolutions than offered by traditional metering devices, smart meters can communicate collected data to external service providers and, thus, enable the creation of novel energy data-based services. Such services include the enablement of ambient-assisted living, generation and demand forecasting, or the provision of recommendations on how to save energy. A fundamental research challenge, still unresolved as of today, is how to fully explore and exploit the information content of smart meter data—a challenge pertaining not only to data processing but equally to their collection, transmission, and security and privacy protection. This Special Issue includes twelve research works and two review papers covering the entire lifecycle of smart meter data.

The first paper in this Special Issue is a comprehensive survey of the state of the art in non-intrusive load monitoring (NILM) by Huber et al. [1]. Disaggregating the power consumption data captured by a metering device has seen a tremendous increase in research interest over the last years. As such, the comprehensive overview of existing technologies, including a comparison of their performance, is an excellent guide for researchers planning to join this research field. Nevertheless, even experienced NILM researchers are likely to discover new methods in this review paper, which may serve as baselines for comparative performance evaluations in their present and future work.

The review paper is followed by a technical NILM contribution by Athanasiadis et al. [2], which differs from existing work in that it is specifically designed to operate on real-time data streams. This not only renders large-scale buffering of data unnecessary but also shows remarkable results on the used dataset. Another interesting observation made during their analysis is the fact that the usage of data sampled at 100 Hz yields a remarkable performance improvement over methods using a baseline dataset, which was collected at 0.167 Hz.

Another technical NILM contribution, leveraging on the application of attention-based mechanisms in deep-neural networks (DNNs), is provided by Piccialli and Sudoso [3]. The proposed approach not only outperforms other DNN alternatives when applied to the two employed datasets, but it is also shown how attention-based mechanisms improve the underlying neural networks' ability to extract and exploit information that would otherwise be ignored (e.g., signal sections with high power consumption).

Although most of the proposed NILM algorithms attempt to disaggregate one load at a time, some authors are also exploring the possibility of disaggregating multiple appliances in parallel. This is the case of the work presented in Faustine and Pereira [4], where a convolutional neural network-based multi-label learning approach is proposed. Experimental results using one public dataset show that the proposed approach significantly outperforms state-of-the-art alternatives to multi-label learning in NILM.

A different application that relies on smart meter data is the detection of electricity theft. A corresponding contribution by Qu et al. [5] is presented next. Theft detection in electrical power grids is often challenging due to the strong imbalance in training data. Usually, only very few consumption traces that contain characteristic patterns of electricity theft are available. The authors have tackled the binary classification problem to discriminate between legitimate consumption patterns and electricity through a combination of clustering and minority oversampling. The proposed method is shown to outperform two existing methods in terms of its theft detection accuracy.

Following up next, a second work on theft detection is provided by Feng et al. [6]. By applying text convolutional neural networks, anomalies in power consumption data can be located quickly and efficiently. By combining data augmentation techniques with realistic datasets, both intraday characteristics and diurnal periodicities are considered in the training process, and remarkable results are reported.

The identification of devices within a building is another exciting challenge that relies on captured electrical voltage and current signals. Wójcik et al. [7] introduce a solution that applies a pulsed voltage signal to attached electrical appliances in order to record their transient responses. Through the creation of a dictionary of transients, their recognition in aggregate electrical load data is facilitated, and the potentials and limitations of the proposed method are discussed.

Another important application of smart meter data, particularly when disaggregated by individual load, is the definition of optimal schedules to optimize energy consumption. With this respect, in Ortiz et al. [8] the authors propose a satisfaction-based energy allocation algorithm that leverages cooperative game theory concepts to determine in which hours the energy should be allocated to maximize energy satisfaction while minimizing the power consumption. Experimental results using a publicly available dataset show that the proposed approach reduced energy consumption by 75%, while increasing the user satisfaction by 40%.

The use of sensor modalities beyond electrical data alone has been investigated by Huchtkoetter et al. [9]. A test bench, on which different electrical appliances-under-test can be operated, has been instrumented with sensors to capture eight ambient parameters in addition to measuring electrical voltage, current, and power. By analyzing the feature importance levels for different categories of appliance types, guidelines for selecting sensor types to increase appliance recognition accuracy were derived and confirmed to contribute to the unambiguous identification of appliances.

Most research works in the domain of smart meter data analytics rely on the use of real-world datasets to evaluate the performance of newly proposed methods and algorithms. A limitation of most existing datasets, however, is the scarcity of annotations and metadata. This limitation can sometimes be remedied through augmenting existing datasets with manual annotations; in other cases, the required aspects must already be considered during the data collection. Both aspects have been tackled by Völker et al. [10]: A new dataset with plentiful annotations, called FIRED, is presented in this work. Moreover, a semi-automated trace annotation tool is presented, which can be used to enrich the annotations of existing datasets. Based on these contributions, more sophisticated evaluations of smart meter data analytics methods become possible.

Another labeled electricity consumption dataset is presented in Renaux et al. [11]. Three different subsets of data comprise the LIT dataset: (1) synthetic, where a controller is used to automatically switch appliances ON or OFF; (2) simulated, where appliance models are used to generate artificial appliance consumption profiles; and (3) natural, where the appliance consumption is monitored and recorded in a real-world environment. In addition to extensive details of the data collection procedures, the manuscript also thoroughly analyzes the consumption profiles in each of the LIT subsets.

Electric vehicle (EV) charging stations have become prominent in electricity grids in the past few years. However, the availability of data regarding EV charging sessions is currently very limited, which poses a significant hurdle to further research in the field. This challenge was investigated by the authors in Lahariya et al. [12], who propose a synthetic data generator to create samples of realistic EV session data, where each session is defined by an arrival time, a departure time, and the required energy. The proposed data generator was trained using real-world EV sessions, and the generated synthetic samples were shown to be statistically indistinguishable from real-world data.

Although electricity smart meters can promote the realization of several services, they can also pose a significant intrusion into a household's privacy. This issue has been investigated by Zhang et al. [13], who propose a privacy-preserving smart metering system that combines data aggregation and data down-sampling mechanisms. Of particular interest is the fact that the proposed system can be adapted to provide different levels of privacy, depending on the requirements and preferences.

The last paper in this Special Issue is a review by Völker et al. [14] that surveys a range of end-user services that can be enabled through smart meter data analytics. The reviewed services include, among others, end-user feedback, anomaly detection, and forecasting of load demand and renewable energy generation. The paper moreover provides a review of the technological foundations and open research challenges in this domain.

The contributed papers that are included in this Special Issue offer new and valuable insights that can stimulate ongoing research activities in the field. As guest editors, we would like to thank all authors who have submitted their contributions to this Special Issue.

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