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Recent advances in the analysis of residential electricity consumption and applications of smart meter data

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HIGHLIGHTS

- Methods and techniques for using smart meter data are analysed; forecasting clustering, classification and optimization.
- End use applications of smart meter data are reviewed.
- Performance of state of the art models are compared.
- Challenges associated with methods and application are identified.
- A new analysis guideline is proposed.

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ABSTRACT

The emergence of smart grid technologies and applications has meant there is increasing interest in utilising smart meters. Smart meter penetration has significantly increased over the last decade and they are becoming more widespread globally. Companies such as Google, Nest, Intel, General Electric and Amazon are amongst those companies which have been developing end use applications such as home and battery energy management systems which leverage smart meter data. In addition, utilities and networks are becoming more aware of the potential benefits of using household smart meter data in demand side management strategies such as energy efficiency and demand response. Motivated by this fact, the amount of research in this area has grown considerably in recent years. This paper reviews the most recent methods and techniques for using smart meter data such as forecasting, clustering, classification and optimization. The study covers various applications such as Home and Battery Energy Management Systems and demand response strategies enabled by the analysis of smart meter data. From a comprehensive review of the literature, it was observed that there are remarkable discrepancies between the studies, which make in-depth comparison and analysis challenging. Data analysis and reporting guidelines are suggested for studies which use smart meter data. These guidelines could provide a consistent and common framework which could enhance future research.

1. Introduction

Early research in residential demand modelling and forecasting mainly focused on a defined geographical region which could range from a city to a particular state, or an entire nation. These approaches were divided into two groups: Top-Down and Bottom-Up. Both have generally been used as tools to assist policy makers and help network operators in planning for future residential energy demand. The Top-down approach uses global scale variables, such as population, GDP, inflation, and national energy statistics, and aims to find relationships with the household stock characteristics, such as appliance usage, penetration rates, building envelope parameters and consumer behaviour [1]. Econometric and regression models are the most commonly used models for Top-Down approach. Previous studies have presented detailed reviews of Top-Down models [1,2].

On the other hand, the Bottom-up approach aims to infer the regional, city, state or national level consumption by studying the household and appliance stock characteristics in detail [3–6]. For example, earlier efforts used detailed household data-sets including dwelling properties, appliance ownership and use information, and demographic and anthropologic information gathered through surveys, in conjunction with historical load measurements and weather data [3–5,7]. Bottom-up models are classified under four main methods: Conditional Demand Analysis (CDA) [3–5,7], Artificial Neural

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Nomenclature

AIC	Akaike Information Criteria
ANN	Artificial Neural Network
ARMA	Auto Regressive Moving Average
ARIMA	Auto Regressive Integrated Moving Average
BN	Bayesian Network
BIC	Bayesian Information Criteria
CV	Coefficient of Variance
CST-LF	Compressive spatial-temporal load forecasting
DBT	Dry Bulb Temperature
DR	Demand Response
DTW	Dynamic Time Warping
FFNN	Feed Forward Neural Network
FMM	Finite Mixture Modelling
GMM	Gaussian Mixture Models
GPR	Gaussian Process Regression
HEMS	Home Energy Management System
HVAC	Heating Ventilation and Cooling
IBR	Inclined Block Rate
LR	Linear Regression
LS-SVR	Least Squares Support Vector Regression
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
MBE	Mean Bias Error
MILP	Mixed Integer Linear Programming
MLP	Multiple Layer Perceptron
MPC	Model predictive control
NRMSE	Normalized Root Mean Squared Error
PCA	Principle Component Analysis
SMBM	Smart Meter Based Model
SI	Solar Irradiation
SOM	Self Organizing Maps
SVM	Support Vector Machine
SVR	Support Vector Regression
STD	Standard Deviation
TVar	Temporal Variables
ToU	Time of Use
RH	Relative Humidity
RMSE	Root Mean Squared Error
RT	Regression Trees
RTP	Real Time Pricing

Networks [8–11], Physical Models [10,12], and Time of Use & Probabilistic Models [13]. Detailed reviews on Bottom-up models can be found in [14–16].

Studies carried out under these approaches commonly worked with monthly, seasonal or annual average demand profiles, with little emphasis on an individual household or appliance's consumption. With the development of smart grid technologies, residential energy modelling and forecasting has gained new objectives. Applications such as Home Energy Management Systems (HEMS), battery energy management systems (BEMS) and demand response (DR) have brought a new focus on individual household and appliance level consumption. These applications require the use of Advanced Metering Infrastructure (AMI), which enables measurement and storage of electricity demand at high resolutions (from seconds to minutes to hours) and allows communication between appliances, households and utilities[1] [17]. Smart meters are a type of AMI and are being installed in households at increasing rates. Recent reports show that 43% of US households owned a smart meter by 2014 [18], while the European Union and Asia Pacific are expecting to have 72% and 58% penetration rates respectively by 2020 [19,20]. A detailed analysis of smart meter deployment across different countries can be found in [21].

Smart meter data can be used in various forms and for various purposes. The use of high resolution and quality smart meter data can be a sufficient resource for residential load forecasting alongside weather variables [22,23]. In addition, smart meter data can give important information about load profiles and habitual consumption patterns. This information can then be used to improve individual or aggregate level forecast accuracy [24,25] or help utilities in determining effective tariff structures and demand response operations [26,27]. Furthermore, smart meter data can be used within home and battery energy management systems which are aimed to organize and optimize the schedule of household appliances in response to user preferences, electricity tariff, demand and distributed energy forecasts [28]. All these aforementioned applications can make demand side management more effective, resulting in lower peak demand and operational costs, while maintaining electricity network system security [29].

There has been a significant amount of research in this area over the last decade, studying various methods and techniques for using smart meter data and its end use applications within the smart grid framework. Table 1 presents an overview of the most recent review studies, mostly falling under the smart grid era. However, these studies have mainly focused on a particular method or a specific end–use application, making it difficult to compare the performance of existing methods and techniques used for a particular end-use application. This review paper follows a different approach, providing a meta-analysis of the literature on the subject. The contributions can be listed as follows:

– A summary and analysis of the most recent, state of the art methods and techniques using smart meter data are presented. In particular, methods used for forecasting household electricity loads, clustering and classification of household load profiles, and optimization of household operations regarding electricity use are examined.
– An extensive review of various end-use applications used in smart grids - such as HEMS, BEMS, DR, market participation, inference of household consumption habits, individual and aggregate demand forecasts - are presented and associated with the aforementioned methods and techniques. As a result, the reader can draw a more complete picture of the area.
– New analysis guidelines are proposed for smart grid studies including forecasting, clustering and optimization in order to allow more direct comparison and analysis between different studies.

The paper is organized as follows; in Section 2, methods and techniques for using smart meter data are described and analysed. In Section 3, various end use applications of smart meter data are discussed. In Section 4, technical and end-use related challenges and recommendations are presented and then some concluding remarks are made in Section 5.

2. Methods and techniques applied to smart meter data

Smart meters can measure household and appliance electricity consumption and depending on the end-use application, they can be utilized by several analysis methods and techniques under forecasting, clustering, classification and optimization objectives. Disaggregation is another method that incorporates smart meter data [45]; however, it remains out of the scope of this paper since it requires more detailed voltage and current readings than the methods described here.

This section analyses the input and output variables, modelling

[1] In previous studies, the term 'utilities' refers to a broader set of institutions including energy retailers, network operators, generators and regulatory bodies. Within this paper, 'utilities' mainly refers to energy retailers and network operators.