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Chapter 4
A comprehensive review on the application of machine learning techniques for analyzing the smart meter data

Abstract: The deployment of smart meters has developed through technical developments. A fine-grained analysis and interpretation of metering data is important to deliver benefits to multiple stakeholders of the smart grid. The deregulation of the power industry, particularly on the distribution side, has been continuously moving forward worldwide. How to use broad smart meter data to improve and enhance the stability and efficiency of the power grid is a critical matter. So far, extensive work has been done on smart meter data processing. This chapter provides a thorough overview of the current research outcomes for the study of smart meter data using machine learning techniques. An application-oriented analysis is being addressed. The main applications, such as load profiling, load forecasting and load scheduling, are taken into account. A summary of the state-of-the-art machine learning–based methodologies, customized for each intended application, is provided.

Keywords: smart meters, datasets, machine learning, deep learning, load analysis, load forecasting, load management

4.1 Introduction

The smart meter is a digital meter used to record power generation and consumption. The characteristics of the smart meter involved in facilitating remote monitoring, control and cutoff by establishing the interface between the utility company and the customer. It was initially called automated meter reading (AMR) facilitating one-way communication and was able to provide monthly reading, one-way blackout,

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tamper detection and simple load profiling. After some time, the AMR ability was increased into recording data on-demand or at hourly intervals and capability of connecting with other commodities. The upgrade in the functionality introduced the term advanced metering integrated (AMI) by the integration of two-way communication; it does not only measure the energy data in real time but it also enables extensive authority and monitoring on both energy and operation situations at both ends, customers and utility companies. The smart meter can be installed at any level of electrical circuits of residential, commercial or industrial buildings [1].

Technological developments have increased the use of smart meters as a replacement of the traditional ones [2, 3]. These meters are key components of smart grids that provide significant civic, environmental and economic benefits to various stakeholders [4]. The massive smart meter installations require a huge amount of data collection with a desired granularity [4]. Automated data acquisition, storage, processing and interpretation are the main factors behind the performance of smart meters. The process is demonstrated in the block diagram in Figure 4.1.

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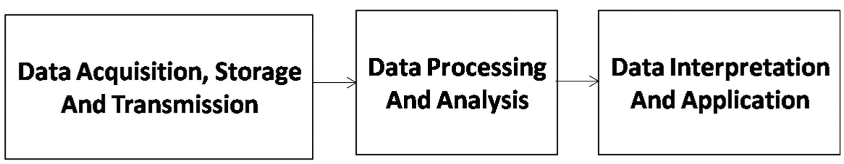

Figure 4.1: Components of the smart meter data intelligence chain [4].

The applications and benefits of smart meters are mainly involved in smart grids due to the necessity to establish an intelligent system for power generation, transmission and distribution. This intelligent approach will address the problems of traditional electric power systems and enable the utilization of clean energy systems such as wind and solar. Due to this enhanced technology, the utility management will be able to possess enough information on peak-load requirements and create pricing mechanisms depending on the consumption requirements [5]. The smart meters benefit the consumers by providing accurate and on-time billing and usage patterns of electrical equipment during expensive hours. This facilitates switch/delay the operation of electrical equipment with significant consumption to less expensive hours. The governments are also profited from the utilization of smart meters by reducing the operating costs and maintaining the security and efficiency of power systems. The smart meters help reduce the extensive disruptions and provide enhanced load forecasting for power sectors [6]. Due to these benefits, the installations of smart meters are increasing yearly in the United States. Based on the research at the end of the year 2018, the power sector companies chose 70% of residents and installed about 88 million smart meters. Also, there is an expectation of reaching 107 million smart meters by the end of 2020 [7]. Additionally, in the European countries, around 34% of all electricity metering points were implemented with smart

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meters (99 million smart meters), and there is an estimation of 24 million for the installation of additional smart meters in 2020 [8, p. 28]. Tokyo Electric Power Company planned a large-scale project to install approximately 29 million smart meters for all customers by the end of 2020 [9]. Kingdom of Saudi Arabia launched Smart Metering Project in 2020 to install around 10 million smart meters, connect these meters into communication girds and generate a fully automated billing process [10]. The government of Dubai started the operation of 200,000 smart meters in 2016 and expected that more than 1 million smart meters will be installed by 2020 [11].

The core technology involved in smart meters is information and communication technologies, which made the infrastructure of smart grids secure and efficient. The achievement of collecting and processing high volume information is made possible by the integration of Internet of things technology with the smart power grids. The types of communication media used between smart meters and utilities are wired and wireless; this differs with different data transmission necessities [12]. First, the transmission of data is acquired from the appliances to smart meters, and second, between the smart meters and the utility's data centers. The communication networks comprise WAN (wide area networks), NAN (neighborhood area networks) and HAN (home area networks). WAN covers a vast geographic zone and transfers the data from the power generation stations to the utilities' central collection center. It can be equipped with wired communication technologies, such as power-line communications and optical fibers, and wireless communication technologies like WI-MAX. NAN covers a smaller geographic zone by establishing communication among neighboring meters. Multiple wireless or wired technologies can be utilized such as power-line communication, digital subscriber line and wireless mesh. HAN interfaces the smart meters with appliances inside the customer premises and home energy management tools. Due to the high demand for electricity in the market, the highest possibility shows that the smart meters will become a part of life eventuality, although one needs to focus on the challenging factors such as deployment process, duration of deployment, operational costs and the availability of the technology [13].

Smart meters and other automated devices that form part of the smart grids can generate massive electrical data. To increase the efficiency of data analysis, it is prudent for these data to be compressed to minimize storage space of data centers and pressure on communication lines. Smart metering entails several approaches such as load analysis, load forecasting and load management. Each customer has a different load profile from the other, for that reason, different patterns can be drawn from the varying consumption of electricity received from various customers. With the necessary insights on the uncertainty and the volatility of varying load profiles, load analysis will help select the accurate data that can be utilized to train a forecasting model. After that, short- and long-term load forecasting is essentially used by the power distribution companies to enhance their planning and operation processes. Moreover, retail providers of electricity develop decisions on procurement and pricing based on the forecasted loads of their customers. The obtained data of smart meters can contribute to the implementation of load management. The management will be able to understand the sociodemographic information of consumers and generate demand response programs to target potential customers [14].

There are several machine learning methods implemented in various residential and industrial applications to improve the functionality of smart meters. A presented case study in the UK is a typical example. The case study has approximately 27 million electrical power customers with a data generation rate of 13,000 records produced per second through the platform Smart Meter Analytics Scaled by Hadoop ~~(Wilcox et al., 2019)~~. Another case study involves Kunshan city in China with 1,312 customers utilizing a fuzzy clustering method and fuzzy cluster validity index (PMBF) to establish load forecasts [15].

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4.2 Contribution and organization

The key publicly accessible smart meter datasets which are used by different smart meter implementations are reported in this chapter. In addition, usage of advance machine and deep learning techniques for efficient smart meter data processing and classification is summarized. Applications like theft detection, nontechnical losses (NTL) and load profiling are taken into account in this context. Machine and deep learning algorithms usage for forecasting of residential, industrial, electric cars and hybrid electric vehicles is also researched and reported. In addition, it also addresses the use of advanced machine learning techniques for automatic load management.

The remainder of the chapter is organized as follows: The current publicly accessible smart meter databases are reviewed in Section 4.2.1. The machine and deep learning techniques used for the analysis and classification of smart meter data are reported in Section 4.3. The use of the smart meter database for load forecasting is addressed in Section 4.4 using machine and deep learning techniques. The load automatic management approaches, built on the basis of machine learning techniques, are eventually described in Section 4.5. Opportunities and challenges are discussed in Section 4.6. Finally, the conclusion is made in Section 4.7.

4.2.1 Smart meter datasets

Many power companies have kept their smart meter data confidential due to privacy and security issues. However, several governmental or nongovernmental organizations took the initiatives to release some residential or industrial data to the public over the past few years. This is in order to assess the researchers to study the performance of smart meters.

4.2.1.1 Commission for Energy Regulation smart metering project

The Commission for Energy Regulation established a smart metering project in 2007 with the help of Irish energy industry participants such as Electric Ireland, SEAI (sustainable energy authority of Ireland) and other energy suppliers. Over 5,000 Irish households and businesses participated on this project from 2009 to 2010 by installing electricity smart meters in their premises. The project aimed to evaluate customer behavior trials on energy consumption patterns. The generated data were available online to researchers on anonymized format without any personal or confidential information [16].

4.2.1.2 Low Carbon London Project

UK Power Networks established the Low Carbon London Project to understand the energy consumption patterns in London. The dataset comprises the operation of 5,567 households from 2011 to 2014 and the records acquired every half hour in kWh. The consumers selected carefully as the representative of UK population and divided into two groups. The first group of approximately 1,100 consumers subjected to different energy prices depends on the dynamic time of usage. The consumers were informed a day ahead of the specific times when the tariff prices would be higher or lower than the normal price. The second group subjected to the standard plan with a constant flat-rate tariff throughout the day. The generated signals will help anticipate the future supply energy operations and lessen the stress on distribution grids [17].

4.2.1.3 Pecan Street: energy research

Pecan Street collaborated with over 1,000 volunteer participants in Austin, Texas, to take a more detailed look at the electricity consumption of residential and small commercial properties. The project installation completed by installing green button protocols, smart meters and home energy monitoring system. The properties were equipped with high-consumed electrical appliances such as cooling and heating systems and other new technologies such as rooftop solar generation, electric vehicle charging and energy storage. The project was aimed to study the effect of these modernizing technologies on the energy loads along with a variation of consumer behavior interventions, including time-of-use pricing [18].

4.2.1.4 Smart dataset for sustainability

The Smart Project commenced a data collection infrastructure in 2012 intending to optimize energy consumption from real households. The project deployed to gather comprehensive data from the household environment rather than gathering data from as many households as possible. The data collection was comprised of electrical, environmental and operation data. The infrastructure supported monitoring average real and apparent power at the main distribution panels every second, average electricity usage at every circuit and nearly every outlet, dimming and switching events from wall switches, average electricity generation from solar and microwind systems and other important binary events from different sensors such as the thermostat, motion and door sensor. The project consisted of two datasets: the first high-resolution dataset (UMass Smart Home) covered a wide variety of traces from three separate smart households. The second low-resolution dataset (UMass Smart Microgrid) covered minute-level electrical data from anonymous 443 households. The data collection and processing were updated in the 2017 release and expected to publish periodic releases of the Smart Home dataset every 6 months [19].

4.2.1.5 Ausgrid distribution zone substation data and solar home electricity data

Ausgrid operated 180 substations within Australian distribution and transmission and the load data for each substation collected by SCADA and metering systems. The historical demand data sampled every 30 min in megawatts. The data might contain a few issues such as occasional metering errors and spikes and dips due to switching within the distribution network. The company is releasing 12 months worth of interval data every year since 2005 [20]. In addition, Ausgrid provided solar home electricity data for 300 residential consumers from 2010 to 2013. The consumers selected randomly without detailed checks for occupancy. The data was measured by a gross metering configuration and recorded every 30 min. Another monthly electricity data from over 2,600 solar homes and over 4,000 nonsolar homes were compiled on a monthly basis from 2007 to 2014. The purpose was to distinguish electricity usage patterns between datasets of solar and nonsolar homes [21].

4.2.1.6 ISO New England – zonal information

New England Independent System Operator (ISO-NE) published load data for eight load zones in the entire New England system since 2011. The publication was made available for the purpose of teaching and researching the power market design and performance in order to help market participants make knowledgeable decisions. The data consisted of hourly day-ahead and real-time demands, daily summaries of real-time demands and monthly summaries of real-time demands. The data was associated with the weather variables, location regional prices, market clearing prices and interchanges with other power systems [22].

4.2.1.7 Tokyo Electric Power Company (TEPCO)

TEPCO had been transparent about both electricity demand and supply. The company provides real-time data sources of historical actual electricity demand data recorded at hourly intervals. These data were available online since 2016 and will be announced with updates each year. Also, the company provides monthly records of daily actual maximum demand, consumption rate in peak usage times and that day's maximum capacity [23].

4.3 Load analysis with machine and deep learning

In a variety of key applications such as NTL detection, theft detection and load profiling the smart meter data is analyzed by using machine and deep learning algorithms. The principle is shown in Figure 4.2.

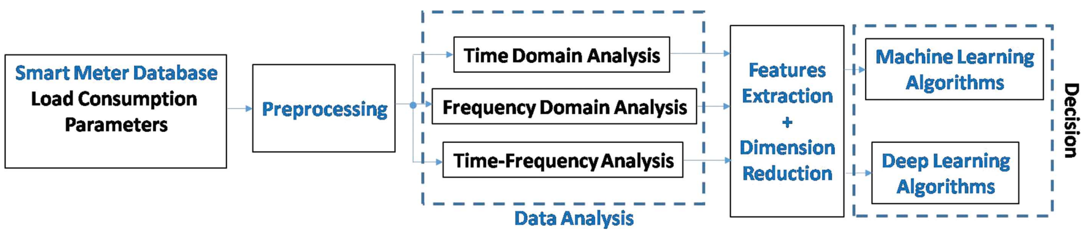

Figure 4.2: Principle of smart meter data processing for load analysis.

Figure 4.2 shows that the smart meter data is first preprocessed to denoise and prepare it for the post-data analysis, feature extraction, dimension reduction and classification modules. The final outcome of the system is in terms of load identification such as home appliances and electric vehicles or classification of losses type such as theft detection and technical losses.

4.3.1 Nontechnical losses

Due to the massive amounts of load profiles at the power utilities, having a better understanding of the volatility and uncertainty of these profiles is a challenging issue. The practice of manipulating electricity data in order to reduce the electricity bill is referred to as electricity theft. It causes a significant loss of energy resources and damages the revenue of power utilities and the overall economy. There are several approaches that had been proposed by the researchers to detect electricity theft by employing, for example, machine learning methods.

The common techniques for theft detection were SVM (support vector machine) and logistic regression. However, these techniques did not work well with large and extremely imbalanced datasets. Therefore, Khan et al. [24] have proposed a novel approach based on advanced supervised learning techniques. The approach involved of five stages: data preprocessing, data balancing, features extraction, classification and validation. Electricity consumption data were preprocessed to resolve the missing and impossible data values, and these data were balanced with the help of ADASYN algorithm. VGG-16 (visual geometry group) module was used for features extraction of abnormal patterns in electricity consumption data. Afterward, the refined features were treated and classified with the help of FA-XGBoost (firefly algorithm-based extreme gradient boosting) module. Various performance metrics were applied to validate the performance of the proposed approach.

Hasan et al. [25] have contributed to the detection of electricity theft by proposing a hybrid model composed of CNN (convolutional neural network) and LSTM (long- and short-term memory). The model was used to explore the time-series nature of the electricity consumption datasets of 10,000 consumers in China over a 1-year period. CNN, which is a subclass of the neural network, was applied for global feature extraction through a number of stacked layers. After that, LSTM used refined features to classify normal consumers and electricity theft consumers. It is a special class of RNN (recurrent neural networks) intended to solve the problem of short-term memory in RNNs. Furthermore, synthetic minority oversampling technique was used to counter the problem of imbalanced datasets and get better performance.

Zheng et al. [26] have presented an approach of two novel data mining techniques: MIC (maximum information coefficient) and CFSFDP (clustering technique by fast search and find of density peaks). This approach combined the advantages of clustering and state-based methods to detect numerous types of theft attacks with high accuracy. MIC was used to find the correlation between NTL and tampered consumer load profiles with normal behaviors. Compared to Pearson's correlation coefficient which can detect only the linear correlation between two vectors, MIC is able to detect more sophisticated correlations such as time-variant relations. Unsupervised density-based clustering CFSFDP was applied to detect the theft attacks that cannot be detected by the MIC correlation method. It defines the density features in order to capture abnormal behaviors of load profiles.

Compared to the existing data-driven electricity theft detection, Gao et al. [27] have developed a physically inspired data-driven proposal to detect theft attacks. The unsupervised proposal used a modified linear regression model to leverage the approximate relationship between the electricity usage and voltage magnitude on distribution secondary obtained from the smart meters. After that, the regression residuals of the estimate to the true consumption were calculated for each consumer. The residuals were used to distinguish both dishonest and honest customer activities. Finally, the anomaly scores were defined for each consumer in order to rank the thieves or identify the consumers with faulty smart meters. The proposal does not require training samples of NTL and a documentation of information topology and parameters.

Sahoo et al. [28] have proposed a novel predictive temperature-dependent model for electricity theft detection instead of the typical methods of load profile analysis of consumers. These methods cannot detect electricity theft in case there is a complete bypass of meters. Therefore, this proposal used the data from branches of distribution systems and smart meters or conventional power meters to detect electricity theft. The proposal started with applying constant resistance technical loss model by correctly identifying the network total losses and estimating the technical losses. NTLs were computed by subtracting the technical losses from total losses. After that, temperature-dependent technical loss model used the temperature dependency of resistances in the consumption points to the distribution transformers.

4.3.2 Load profiling

Zhu et al. [29] proposed a method to measure the daily load behaviors and to classify irregular energy consumption. Their method consists of three core phases. The first phase is preprocessing the time series of a high-frequency building load into a variety of important statistics [29]. These statistics are divided into two groups: one group is about the load profiles taken from the building such as average daily load, the minimum and maximum load, the median load, near-base load, near-peak load, high-load duration, rise time and fall time [29]. The other group is about the daily weather conditions such as the mean, mode, median, minimum and maximum of the temperature and humidity. The second phase is constructing the prediction models. This phase requires two actions: firstly, choose the best method for mining the information to obtain the best example from training data. Secondly, choose the most appropriate predictor to construct the model [29]. The authors constructed three predictors for cooling, heating and seasonal transitions. The last phase is evaluating the residues of chosen prediction models based on the concept of statistical quality control. They built a control table for every load profile with a suitable upper bound. Then these charts of control are used to track everyday load profiles and classify irregular energy usage [29]. Real-world building and weather information computing experimental results show that their proposed model and methods are successful. Their approach is easy to integrate in current energy management systems in buildings and needs no complex submeters.

Stephen et al. [30] presented multiple models of linear Gaussian that can predict efficiently many patterns that are typically thought to be homogenous for residential customers. The combination of the modeling strategy and the smart meter advance data has allowed a representation that not only expresses load magnitudes at a given time of day but also their variability and how these variabilities influence other times of use. The mixture model frame in which the mixture is inserted enables the most likely predictive use of multiple behaviors in order to categorize a given home consumer on a given day. In this case, complex consumer behavior patterns can be recorded as they grow with seasons or differences in activity. These models have theoretical properties that allow the ready application of sampling techniques to illustrate precision gains compared to existing load profile strategies. These developments are important to the management of smaller and insular power systems. Loss of output in the MFA model may have been due to over-fitting of the covariance matrices.

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Intelligent meters generate detailed data on energy usage. In intelligent power grids, it is very difficult to model energy consumption at each node, especially for systems that require linear processing of the nonlinear data. Khan et al. [31] introduced to use a series of weighted linear profiles to provide a new way to stochastically model extremely nonlinear smart meter data patterns. An advanced algorithm for clustering data with a high intrinsic pattern is designed to obtain energy consumption profiles. Compared to ordinary linear approximations without losing precision, the method linearizes nonlinear energy knowledge with certain linear profiles. In this research paper, the reliability and accuracy of the approach were continuously demonstrated, taking into account the multiple cluster cases and repetitive testing. The advantages of this approach include extracting patterns that are close to high intracluster patterns, transforming extremely nonlinear functions to linear functions, reducing smart meter huge data and reducing process time. The method allows the analyzer of nonlinear charges through linear analytical methods and increases the flexibility to model the systems of smart grid simulation.

4.4 Load forecasting with machine and deep learning

In potential applications and services, it is required to forecast the requirement of different load types such as industrial load, residential load and electric vehicles. It can be effectively achieved by using the modern machine and deep learning approaches. The principle is shown in Figure 4.3.

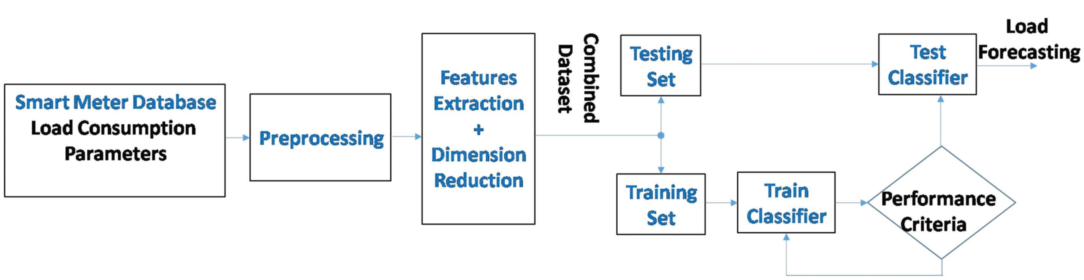

Figure 4.3: Principle of smart meter data processing for load forecasting.

Figure 4.3 shows that the smart meter data is firstly preprocessed to denoise and prepare it for the post-feature extraction, dimension reduction and classification modules. The overall dataset is tactfully divided into two parts: testing set and training set. The training set is intelligently used to train the intended classifiers while targeting the performance criteria such as accuracy and noise thresholds. Once the chosen performance criteria are achieved, then the trained classifier is used for load forecasting based on the testing dataset. Categories of loads such as residential, industrial and electric vehicles are frequently forecasted by such approach.

4.4.1 Residential load forecasting

Load forecasting has become increasingly crucial for the energy consumption of residential consumers. The consumption at the residential level is much more irregular than the transmission or distribution levels. In addition, it has a high correlation with many variable factors like resident behavior, household size, individual loads, weather conditions and many other factors.

Different statistical and machine learning techniques can be used in order to figure out a suitable prediction algorithm. Shabbir et al. [32] compared the performance of three machine learning algorithms in load forecasting: linear regression, tree-based regression and SVM-based regression. The linear regression simply modules the relationship between the dependent variable and several independent variables. The tree-based regression works very well with a large number of variables and module higher order nonlinearity and great interpretability. However, SVM was found to perform accurately compared to the other algorithms as it uses more observation values. The performance is validated in terms of RMSE (root mean square error) value.

Humeau et al. [33] adopted linear regression, SVR for regression, and MLP (multilayer perceptron) for residential load forecasting at individual meter level and aggregate level. Compared to these algorithms, the linear regression delivered a high performance on forecasting at the level of single household load. Nevertheless, SVR and MLP perform better on forecasting aggregated load than a single household load. It determined an aggregation size (which is 32 households in this study) at which SVR starts to outperform linear regression. The forecasted values were evaluated with MAPE (mean of average percentage error) and RMSE as well. Normalized RMSE values decreased with the increase in the number of households in clusters.

Ahmadiahangar et al. [34] introduced the generalized linear mixed effects module, which is a machine learning–based regression module. It defines the correlation between a response variable and independent variables using coefficients. The module generates load patterns and predicts the possible flexibility of residential consumers. Different examples of load patterns can be generated from regression modules such as getting load patterns for a longer period or getting separate patterns for workdays and holidays. It is possible to achieve a detailed prediction by studying the patterns between different residential applications. The advantage of this module is that it can be used in online and real-time control approaches.

Jetcheva et al. [35] presented a building-level neural network-based ensemble module for a short-term (24 h ahead) and a small-scale electricity load forecasting. Each neural network predicts the load for a specific time point, and the set of predictions will form the load prediction of the whole day. The neural network architecture for individual networks composes the ensemble module trained with different subsets provided by a preceding clustering in order to find the most suitable combination of variables for the module. The module performance was compared with the SARIMA (seasonal autoregressive integrated moving average) module, as it produced up to 50% higher forecast accuracy. However, SARIMA is a linear statistical module that might not be able to predict high nonlinear residential loads.

Kong et al. [36] proposed a framework of a deep LSTM recurrent neural network for short-term residential load forecasting. This framework addresses the high volatility and uncertainty of residential loads. Some household daily profiles can be organized into major clusters and others do not have clusters at all. The authors compared the forecasting performance of two cases, aggregating the individual forecasts at the household level and forecasting the aggregated load at the system level. The result shows that aggregating all individual forecasts yields to precise forecasting than directly forecasting the aggregated load. LTSM performance benchmarked with the conventional BPNN (back-propagation neural network). LTSM performed better with single-meter load forecasting as it can establish a temporal cooperation with loads on high level of granularity.

Lusis et al. [37] examined calendar effects, forecasting granularity and length of training dataset that affect the accuracy of residential short-term forecasting. Forecasting techniques such as MLR (multiple linear regression), regression trees, SVR and artificial neural networks (ANNs) were typically trained and tested. RMSE and normalized RMSE were applied as forecast error metrics. Combining the seasonality and weather data with the load profiles yields a very low forecasting performance for calendar effects. An increasing number of households might smooth the load profiles and enhance the forecasting of periodic load patterns. Furthermore, forecast errors can be reduced by using coarser forecast granularity, increasing forecast intervals and training datasets. Support vector regression showed better performance on the accuracy of one-day-ahead forecasting.

Kong et al. [38] studied occupant's life patterns to achieve high forecasting performance at the household level. The specialty of this study was integrating appliance-level consumption at a single household to train the LSTM module. Feed forward neural network and k-nearest neighbor regression utilized to validate the performance of LTSM. The module improved the forecasting performance and established a temporal correlation between consumptions over time intervals.

4.4.2 Industrial load forecasting

The accuracy and robustness of forecasting industrial load profiles are difficult to be implemented due to variable factors. These variables could be load measurements, scheduled processes, manufactured units, work shifts, weather conditions and so on. This will result in improving the energy efficiency and reducing the operational costs by managing electricity consumption and planning the production and maintenance schedule.

Almalaq and Edwards [39] have introduced famous deep learning algorithms that applied to the forecasting of smart grid load. The algorithms are autoencoder, RNN, LSTM, CNN, RBM (restricted Boltzmann machine), DBN (deep belief network) and deep Boltzmann machine. RBM consists of two layers for hidden units and variable units and with the restriction that there is no connection between variables on the same layer. DBN architecture has several layers of hidden units called stacked RBM, and it is trained with a backpropagation algorithm. The architecture of DBM has stacked RBM as well but with bidirectional connections between every two layers. These algorithms showed a great percentage of error reduction for load forecasting. For instance, combining autoencoder with LSTM predicted renewable energy power plants, CNN with k-mean clustering predicted short-term summer and winter forecasting and DBM predicted wind speed for the smart grid. Ensemble DBN with SVR had the highest error reduction compared with other methods.

Park et al. [40] have suggested the necessity for short-term load prediction to operate power generation and CCHP systems (combined cooling, heating and power) efficiently. The approach consisted of two stages: two single algorithms used in the first stage, which are gradient boosting and random forest. These algorithms generate better prediction accuracy as gradient boosting can work with different loss functions and random forest can manage high-dimensional data well. However, the over-fitting during training occurs with gradient boosting and the average of all predictions from the subset trees form with random forest. Due to these reasons, the prediction accuracy of these single algorithms will be affected. The predicted values are used as input variables to train the deep neural network (DNN) model and enhance the prediction performance. This is in order to take advantage of each algorithm and expand the domain of applicability and coverage. Several machine learning methods are used to demonstrate the proposed approach predicting one-day ahead on a factory electric energy consumption dataset. It showed the best performance in terms of coefficient of variation of RMSE and MAPE (mean absolute percent error).

Ahmad et al. [41] have presented an accurate and fast converging one-day load-forecasting model for industrial applications in a smart grid. The model is based on MI (mutual information) for feature extraction and ANN to forecast the future load. The inputs of historical load time series ranked through the MI. After that, the ranked inputs passed through filters to remove redundancy and irrelevancy. The selected inputs of more relevant information are given to the ANN to generate training and validation samples, and thus forecast the load of the next day. Finally, the enhanced differential evolution optimizer reduced the overall forecast error. The limitation of this model is that it was not designed to forecast the load of 2 or more days ahead. In addition, the convergence rate was improved but at the cost of accuracy.

Hu et al. [42] have proposed a forecasting model for a short-term electric load in the process industry. This will help to optimize electricity consumption and reduce the operation cost. BPNN model was hybrid with GA (genetic algorithm) and PSO (particle swarm optimization). In order to address the drawback of BPNN falling into local optimum, combining the local search function of GA and the global search function of PSO will be necessary. GA and PSO optimize the weights and thresholds of BPNN due to the overfitting problem and after that BPNN will perform the forecasting task. PSO-BPNN and GA-BPNN implemented and compared with the hybrid GA-PSO-BPNN. The proposed model proved with the highest accuracy and low MAPE value.

Porteiro et al. [43] focused on studying different models for forecasting the next hour load. With the optimized model for single hour prediction, a hybrid strategy was applied to build a complete 24 h ahead hourly electricity load-forecasting model. The hybrid strategy combined both direct strategy and recursive strategy. The direct strategy develops different forecasting models for each time step to be predicted and it eventually requires a heavier computational load. The recursive strategy develops one-step forecast multiple times and it ultimately allows prediction errors to accumulate. Extra trees were selected as the best method for forecasting the next hour with the lowest training time. The complete model was evaluated against MAPE and showed its effectiveness in addressing the 24 h ahead of industrial demand forecasting.

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Bracale et al. [44] developed a set of MLR models for forecasting industrial loads 24 h ahead for a factory that manufactures MV/LV transformers. The past measurements recorded at a 15-min interval as candidate quantitative variables and processed through the MLR model. Other candidate qualitative variables included as well such as hour of day, type of day and work shift. Interactions between variables were suggested, and the interaction effects between past measurements of power and calendar variables were found to be effective. MLR performance benchmarked with SN (seasonal naïve) and MLR-B model. SN assumed that the unknown load is the same as the observed load measured at the same time in the last season. Normalized mean absolute error and normalized RMSE were used for validation and testing procedure.

Kim et al. [45] addressed the issue of the data absence in small industrial facilities due to the lack of infrastructure. The authors developed a generalized prediction model through the aggregation of ensemble models for peak load forecasting. The industrial datasets were nonstationary with different statistical characteristics; thus, it is impossible to develop a generalized prediction model using a single time-series analysis technique. Machine learning methods such as ExtraTrees, bagging, random forest, AdaBoost and gradient-boosting failed on load prediction in terms of RMSE and MAPE and verified that past data cannot be used as prediction variables. Therefore, the proposed model utilized the load pattern in the same day to construct powerful predictor with combining bagging and boosting methods into several decision trees. However, the forecast performance was still weak for practical environments.

4.4.3 Electric vehicles load forecasting

Many studies have been done proposing new approaches for load forecasting. Dabbaghjamanesh et al. [46] presented a Q-learning method for the plug-in hybrid car load forecasting relying on the ANN and the RNN. The Q-learning method uses Markov decision processes, which determine the best approach between all possible actions. Q-learning is considered as one of the model-free enhancement learning methods [46]. The forecasts for the ANN and RNN techniques for previous days should be used to apply the Q-learning method for predicting plug-in hybrid car load [46]. The Q-learning method, based on the findings of ANN and RNN, picks the best possible action to forecast the plug-in hybrid car load for the next 24-h horizon to find an optimal prediction of the plug-in hybrid car load. Various types of plug-in hybrid cars were used by the authors such as intelligent, coordinated and uncoordinated [46]. Their results show that plug-in hybrid cars charge can be accurately predicted by the Q-learning method that is based on ANN and RNN information [46]. Their simulation results proved that the Q-learning method reliably predicts the load for the plug-in hybrid car more than the ANN and RNN methods [46]. When comparing between Q-learning and ANN and RNN under the worst charging case of plug-in hybrid cars, the Q-learning achieves more than 50% improvement over ANN and RNN methods [46]. The suggested methodology for Q-learning will generally monitor the plug-in hybrid cars load more quickly, reliably and flexibly than the ANN and RNN methods [46].

Mansour-Saatloo et al. [47] have followed the transformation of the energy market and the introduction of the plug-in electric cars by proposing a new approach for the load forecasting of the plug-in electric cars [47]. They used one of the machine learning techniques called generalized regression neural network. For training, the researchers used old data on the arrival and leaving times of the plug-in electric cars as long as it could approximate the distance driven by each electric car [47]. Moreover, to extend the data based on suitable historical data on a suitable distribution function, the Monte Carlo simulation was used in this research [47]. The system was improved following training and testing by learning the movement pattern of each electric car, which is used to forecast the distance of new electric cars traveled. New data with 98.99% precision, mean square error of 1.3165, root mean square error of 1.1474 and mean absolute error of 0.8199 errors were predicted by the system [47].

Four deep learning techniques were used by Zhu et al. [48] to forecast the short-term charging load of real electric car charging stations in China. The four techniques are the DNN, RNN, LSTM and gated recurrent units. The database used in their research was a big data platform of a company that has a large proportion of electric car charging stations in China. Their findings indicate that the methods clearly proven their efficiency on the database. In comparison with the other three methods, the gated recurrent unit method with one hidden layer achieved the best performance [48]. These findings cannot, however, indicate which method in the application has the absolute advantage. The key explanation to that is that the model training used only restricted data of one charging station [48].

4.5 Load management with machine and deep learning

Many studies have been done on load management; the following is a review of some recent ones. Nan et al. [49] introduced a smart home group demand response scheduling model focused on the residential load transmission through load aggregator [49]. Demand response has been extensively deployed in recent years as the key tool for communicating between the power grid and the consumers for developing the energy market [49]. In conjunction with the interruptible load program, the model program efficiently programs the residential loads under various demand response programs [49]. The purpose of their model is to reduce the usage of electricity by the consumer [49]. The whole group of demand response services is optimally planned under various demand response programs, without interacting with consumer convenience, which lowers user energy costs and at the same time reduces the residential peak pressure, the peak load and the energy usage [49]. Their model greatly stimulates the demand response potential of the residential population. Furthermore, from what the study suggests, it can be noted that an analysis of the expected charge curves can be carried out to examine various demand response programs that can determine an optimal demand response program [49]. The model can therefore help in the determination of electricity prices in line with the growth of the electricity markets [49].

Another study was done by Ahmed et al. [50] using a new binary backtracking search algorithm to handle energy consumption with a real-time home energy management system optimal schedule controller. In order to restrict total load demand and to plan home appliances service at certain times during the day, the binary backtracking search algorithm provides an optimal schedule for home devices [50]. Smart socket hardware model and graphical user-to-interface applications were developed to illustrate the suggested home energy management system and to provide the load-to-scheduler interface [50]. A number of household appliances most frequently used were considered regulated, including air conditioning, water heaters, fridge and washing machine [50]. They implemented their suggested scheduling algorithm in two cases where the first case takes account of operations during the week from 4 PM to 11 PM [50]. For the sake of checking the precision of the established controller in the home energy management system, the researchers compared their experimental results with binary PSO schedule controller [50]. The binary backtracking search algorithm achieved better results in lowering the electricity usage and the overall energy bill than binary PSO schedule controller and saves energy at high loads. The binary backtracking search algorithm schedule controller achieved energy saving of 4.87 kWh a day on weekdays and 6.6 kWh a day on weekends (26.1% a day) [50]. The binary PSO schedule controller's energy saving results are 4.52 kWh/day (20.55% daily) on weekdays and 25% on demand response hours (6.3 kWh/day) [50].

Another study presented by Adika and Wang [51], who proposed both appliance scheduling and smart charging techniques to households' electricity management. By autonomous response to price alerts, the programming of electric appliances by the smart meter was obtained [51]. Electric consumers also should not be involved in demand side management directly [51]. This method has been used with the idea of an aggregator for the synchronization of appliance energy demands and the introduction of an intelligent cluster-based storage charging based upon a daily price forecast [51]. Consumer loads and their related batteries are divided into clusters that synchronize load patterns with their respective electricity consumptions with the pricing system for the day [51]. Their findings indicate that the consumers can save substantially on their electricity bills with sufficient scheduled storage equipment and carefully planned real-time prices [51]. The storing of electricity reduces the peak to average grid load and thus therefore helps the providers of electricity. The proposed method presented an effective electricity management approach particularly for residences with adequate and accurate historical load and electricity price data. Uncoordinated battery charge and discharge could, however, threaten grid stability and lead to customer indifference. Thus, the storage devices must be operated effectively to ensure that every electricity consumer receives full and equal value [51].

4.6 Discussion and challenges

The smart meters are used in real time for calculating power usage at the finest granularities and are seen as the basis of the future smart grid technological developments that have evolved the utilization of smart meters, instead of traditional ones.

Such meters are the essential elements of smart grids and provide important advantages for various stakeholders. These multitude of advantages can be categorized as social, environmental and economical. The massive installations of smart meters are producing a large volume of data collection with a desired granularity.

Automated information collection, storage, processing and classification are the main factors behind the performance of smart meters.

The collection of fine-grained metering data is important to give practical advantages to several stakeholders of smart grid in terms of performance and sustainability. There are different goals for different stakeholders: vendors, for example, would like to reduce the operating expenses involved with traditional meter reading and significantly increase the loyalty of the consumer. The operators of the transmission systems and distribution networks want to take advantage of a more robust demand side that enables lower carbon technology penetration. Governments aim to achieve the objectives of reducing the carbon emissions by increasing the energy efficiency in the consumer side, which is given by smart meters. Consumers are having better awareness of energy. Therefore, they are expecting to benefit from the reduced electricity bills. With these goals, it is not surprising that smart meters are having a faster growth period.

From a generalized viewpoint, identifying the type of device is a difficult task because of the several reasons. Firstly, there are possible overlaps among a wide variety of types, for example, laptops and tablets. Secondly, there is a wide range of devices that fall under the same group because of their unlike operating mechanisms and technical changes that occur among appliances. Generally, the appliance identification must guarantee the precise ability to simplify without exceeding a certain number of appliances.

In a number of uses, the data collected through smart meters are analyzed. A smart meter's performance is dependent on algorithms that can run and to perform real-time intelligent operations. A smart meter chipset module can perform the appropriate function by programming within hardware limitations. The smart meter processor typically performs multiple tasks such as measuring electricity, showing electrical parameters, reading smart cards, handling data and power, detecting malfunctions, interacting with other devices.

To consumers, one of the key benefits of smart metering is to help them conserve more money. Comprehensive knowledge on usage would allow consumers to make better decisions on their schedules for energy use. Despite the recent increases in electricity prices, consumers should move their high-load household appliances to off-peak hours in order to reduce their energy costs and billing. One feature that would help the consumers directly is the applications that can offer details on intermittent electricity and overall energy consumption. In this context, the data can be collected on hourly basis, daily basis or weekly basis. Another useful use for energy disaggregation is to break down the gross power consumption of a household into individual appliances. In this way, the consumer will be aware about how much energy every appliance uses to help them control their consumption better.

Smart metering services would allow the distribution system operators (DSOs) to properly control and sustain its network, and more effectively deliver the electricity, while reducing its running costs. Automatic billing systems will decrease billing-related concerns and visits to the site. It helps the dealer to remotely read the consumer meter and to submit correct, timely bills without daily on-site meter readings. This also offers a two-way link that allows detection and management of the remote issue possible. Energy stealing is one of DSOs' most critical issues, which causes a major profit deficit. A variety of methods for the prevention of energy theft have been suggested by incorporating the AMI into electrical power systems [52].

The installation of smart meters often poses many obstacles, while adding important benefits to the community. One of the challenges in deploying modern metering technology is from an economic standpoint. The AMI's construction, implementation and servicing entail several problems and include budgets of many billion dollars for deployment and servicing. Therefore, a cost–benefit study will be a fair starting point for potential smart metering infrastructures to develop. The advantages can be distinguished between those who are primary and secondary. Primary benefits are that which will specifically influence the bills of consumers, while indirect benefits are in terms of efficiency and changes in environmental standards and would have potential economic impacts. In [53], the current value of potential profits with respect to costs is analyzed while presuming a project life of 13 years, including 3 years of execution and 10 years of service. It is reported that, by considering both primary and secondary economic advantages, smart grid provides a favorable economic benefit if the obtained profit-to-cost ratio is between 1.5 and 2.6. There are also protection and privacy issues. Customers collaborate together with the utilities through the installation of smart meters and two-way communication capability to control electricity consumption. The details they exchange shows consumer preferences and behaviors, how they use electricity, the number of people in their homes and the devices in use that subject them to privacy breaches. In a smart grid context, a stable and scalable distributed computing network is required. In this viewpoint, one of the big challenges is to make real-time data accessible from smart meters to all the stakeholders who use these details to meet those requirements.

The use of smart meter data is also growing in other applications, in addition to the load analysis, load forecasting and load management applications. Other potential applications are power network link verification, failure management, data compression and privacy analysis.

Although considerable attention has been paid to smart meter data analytics and rich literature studies have been published in this field, advances in information and communication technologies and the energy grid itself will undoubtedly lead to new challenges and opportunities. The big data dilemma is one of the main issues. This is due to the multivariate convergence of data such as economic statistics, meteorological data and charging data for electric vehicles, apart from data on energy usage. In addition, integration of the bidirectional and efficient smart grid with distributed renewable energy sources and electric vehicles is another obstacle. Additionally, maintaining the confidentiality of smart meter data is another important problem. Several encryption algorithms and secure communication architectures have been proposed in this context.

4.7 Conclusion

The recent technological advancement in Internet of things, informatics and communication is evolving the deployment of smart meters. In this chapter, a review of the latest research findings in the use of advance machine and deep learning approaches for the smart meter data analysis is presented with an application-oriented analysis. The major applications are taken into consideration such as load analysis, load forecasting and load management. A description of state-of-the-art techniques and methodologies for machine learning tailored for each considered application is presented. It is also addressed that smart meter data will be used for other possible uses in the future, such as verification of power network links, failure control, data compression and analysis of confidentiality. In the framework of smart meter data analysis, key upcoming issues such as big data, incorporation of distributed renewable energy sources, electric vehicle to grid connectivity, and data privacy and security are also identified. The analysis of smart meter data is a new and exciting research field. We hope that this study will provide suitable information to potential readers about smart meter data analysis based on machine learning and deep learning techniques, its applications and upcoming challenges.

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