ANALYZING ELECTRICITY CONSUMPTIONS PATTERN FOR PROFILING AND FORECASTING: A REVIEW

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Abstract

The smart electricity meters are electronic devices of smart grid systems which record the use of electricity or consumption in real time. In the present scenario, the demand and supply of electricity are growing at an invariable rate throughout the residents and make use of for various purposes like household appliances, industries, agriculture, hospitals etc., so, it is becoming more and more complex to manage the electricity supply and consumption. Electricity Consumption varies by consumers which depends on several factors including weather, time, and socio-economic constraints, etc.. Smart electricity meters render an automated collection of fine-grained (usually taken at every 15 minutes or hourly) consumption data. Data caused by these electrical systems, it is possible to derive electricity consumption usage and patterns using variously available data analytics and mining techniques. The consumer profiles and clustering of consumers based on their behavioral correlations can be obtained through these generated consumption usages and patterns. With the guidance of individual and aggregated profile, load forecasting is also possible. In this paper, authors have presented a literature survey for algorithms and technologies used in smart electricity meter data analytics which focuses on electricity consumption usage, pattern, profile and load forecasting.

Keywords: Smart meter, Data analytics, Data mining

1. INTRODUCTION

AMI (Advanced Metering Infrastructure) which is the vertebrae of the smart grid and is the combined term to describe the whole infrastructure from Smart Meter to two way-communication networks to control center equipment and all the applications that enable the collection and transfer of energy usage information in real-time [20]. Smart metering systems endeavor many operational profits for energy utilities and policymakers, including

- permitting an automated collection of fine-grained (usually taken at every 15 minutes or hourly) consumption readings, thereby reducing the necessity for utilities to send out estimated bills or to send personnel to consumer premises and manually read the meters,
- facilitating effective pricing plans that depend on the time-of-day in order to decrease demand for electricity

Smart metering systems are increasingly adopting the Internet of Things (IoT) such that huge amounts of energy generation and consumption data are produced, assembled and stored. Due to its huge amount of data, it becomes difficult to be processed by traditional techniques. This provides the opportunity to execute data mining and analysis techniques to find electricity consumption patterns of residential and commercial users in terms of the time of electricity use and the amount of electricity consumption. This has introduced an area named Data Analytics for Smart Meter which becomes an active research area in power industry. Some of the core purposes to this research area are as below:

- Energy theft detection
- Select best service provider to enhance customer satisfaction

- Diminish billing errors by more accurate measurements

As per the usage of electricity, Electricity consumption patterns of a consumer may vary significantly within consumer groups due to various factors like weather condition, temperature, their lifestyle, etc. It is difficult to discover the behavioral attributes of consumers without advanced data analysis and mining techniques. From the analysis of electricity consumption patterns, user electricity consumption profile can be formed.

On the basis of electricity consumption usage and patterns, the new challenges as well as opportunities to load forecasting also comes out for this research area. According to different forecast extents and resolutions, Load forecasting is classified into three categories i.e. short-term load forecasting (1 hour to 1 week), medium-term load forecast (1 week to 1 month), long-term load forecast (month to years). From these categories, Short term load forecasting using smart meter data is very much important which intensely affects the resource planning and control operation of the power utility.

2. LITERATURE SURVEY

Literature Survey on Data Analytics of Smart Meter work associated with the generating the consumer usage and patterns using the time series data shows the usage behaviors of consumers. With the help of clustering of consumption patterns using various clustering algorithms, it is possible to generate consumption profile for each cluster. While generating consumption profile, consumer usage and pattern various factors like weather condition, temperature, their living lifestyle, usage time, day type etc. comes into the analysis. Consumption profiles are used in numerous analytical applications such as load control, load estimation, load forecasting, pricing judgment, detecting unusual energy consumption and developing power market policies. Out of the mentioned analytical applications related work is described as below:

2.1. Energy Consumption Usage and Patterns

Electricity consumption patterns of the consumer can vary significantly within consumer groups. It is difficult to determine the behavioral symptoms of a particular consumer without advanced Data analysis and mining techniques. Based on the consumer's household consumption pattern, consumer energy consumption profile can be generated using various data analytics and mining techniques.

In [3], authors has presented and evaluated an approach that leverages electricity smart meters as occupancy sensors using stateless and stateful classification algorithms where stateless classifiers were Support Vector Machines (SVM), K-Nearest Neighbor (KNN) and Thresholding (THR) and stateful classifier was Hidden Markov model (HMM).

Authors have explored Fuzzy c-means (FCM) clustering method and a fuzzy cluster validity index (PBMF) to generate electricity consumption patterns of low-voltage residential consumers in China [6].

A benchmark for understanding the effect of external temperature on consumption to find consumption usage andpatterns has been proposed by authors using the 3-line algorithm [9].

A set of unsupervised machine learning techniques like Hierarchical cluster analysis, Grade Data Analysis, Sequential Association Rules, C-Means Clustering, and Multidimensional Scaling have been introduced and implemented by authors to exhibit specific consumption usage patterns observed at an individual household [10].

2.2. Consumption Profiles at Individual and Aggregated level

Electricity consumption profile formation of consumer is a fundamental operation of smart meter data mining through which electricity providers and consumer can achieve various tasks like

- Conducting virtual electricity audits for saving consumption usage
- Offering personalized suggestions for saving electricity based on the trends identified in the profiles
- Clustering households based on the characteristics captured by the consumption profiles
- Forming real-time alarms if new consumption readings do not match the expected consumption predicted by the profiles

Based on temperature and weather effects, Hidden Markov framework for generating individual and aggregated consumer profiles have been used to propose a state machine for electricity consumption [1].

Authors have applied a time series auto-regression model, specifically Periodic Auto Regression with eXogenous variables (PARX) for residential consumers using various electricity consumption at different times of day and at different external temperatures to generate simple, easy to understand and effective profiling framework [2].

K-means was chosen to form the cluster based on the consumption usage [5]. To extract key-data signatures out of the smart meter data with different time resolutions authors have presented various methodologies [8].

Authors have set a standard which has used Periodic Auto Regression (PAR) algorithm to extract consumption profiles of consumers and the time series similarity search algorithms to find similar consumers to form cluster [9].Authors have presented how R can be used to see daily, monthly and quarterly consumption pattern and profile based on consumers' usage [11].

2.3. 3. Load Forecasting

Load Forecasting based on electricity consumption usage and patterns is an extensive task to provide intelligence to the smart gird. Research on short-term load forecasting has a long history. Many experts and scholars in India and abroad have done research work in terms of forecast theory and method and based on that many forecasting models were introduced. For the residential load for different sampling periods and forecasting horizons, authors have used Kalman Filter method for the predication of electricity consumption [4].Authors have explored on System load which was obtained with the help of load forecasting calculated from the different clusters which are generated using load forecasting model based on Online Sequential Extreme Learning Machine (OS-ELM) [5].

Authors presented an approach to forecasting electricity consumption load on an individual household using Support Vector Machines (SVM) and Multi-layer Perceptrons(MLP) were evaluated by computing the accuracy measures between the observed and predicted values, where the SVM and MLP are types of feed-forward neural network which can potentially provide greater intelligence to the smart meters and value added for individual customers [7].To forecast average electricity load for every hour on daily basis using Smart Meter data using Artificial neural network (ANN) technique was proposed in [12].The multiple linear regression, step-wise linear regression, neural network method, and enhanced the neural network to forecast the short term load were presented in [13].

Deep Neural Network (DNN), as well as other machine-learning techniques like linear regression (MLR), regression trees, support vector regression were used to short-term load forecasting in a power grid was introduced by authors [14].Authors have explored on how forecasting of the aggregated residential load was calculated using Long Short-Term Memory (LSTM) Recurrent Neural Network (RNN) based framework [16].Two non-seasonal and two seasonal sliding window-based Auto-Regressive Integrated Moving Average (ARIMA) algorithms were presented for short-term forecasting of hourly electricity load [22].Authors have studied how calendar effects, forecasting granularity and the length of the training set influence the precision of a day-ahead load forecast for residential consumers using time series model i.e. Seasonal ARIMA(p,d,q)- (P,D,Q) model with exogenous variables (SARIMAX) was considered in [22]. With the help of Apache Hadoop and R, analysis of time series smart meter data by applying ARIMA and ARMA models to forecast the demand for electricity have been introduced [11].

3. Algorithm used in Data Analytics for Smart Meter Consumption Data

3.1. Fuzzy c-means (FCM) clustering

The purpose of data clustering is to partition a given data set into discrete groups based on the similarities between data objects so that the data objects partitioned into the same group are as similar as possible and the data objects in different groups are dissimilar to the maximum degree [6]. Through FCM clustering, clusters were formed and typical electricity consumption profiles were achieved when the number of clusters was set to three, eight, and ten.

3.2. PARX

PARX which is auto-regressive time series modeling with eXogenous variables to produce consumption profiles which consider various factors influencing electricity consumption, such as temperature and the consumers' daily usages but the limitation of the proposed approach is that it is effective only for regions where some fraction of household electricity consumption is correlated with temperature [2].

3.3. Hidden Markov Model

Authors have demonstrated a methodology based on Hidden Markov Model which builds dynamic consumption profiles based on temperature for individual and aggregated consumers and also addressed how this methodology may be used in exercise to understand consumption and its components mainly driven by response based on outside temperature [1]. A stateful classification algorithm Hidden Markov Model was assessed which leverages electricity meters as occupancy sensors who performs best amongst households producing accuracies over 80% was presented in [3]. Authors motivated by the necessity of reducing the energy consumption for cooling and heating in residential buildings using Hidden Markov Model[17].

3.4. AutoRegressive Integrated Moving Average (ARIMA)

An AutoRegressive Integrated Moving Average (ARIMA) model is a generalization of an AutoRegressive Moving Average (ARMA) model where both are fitted to time series data either to properly understand the data or to predict future points in the series.

Authors have presented two non-seasonal and two seasonal sliding window-based ARIMA algorithms which are further evaluated into four incremental non-seasonal and seasonal (S)ARIMA algorithms which are Sliding Window Hourly ARIMA Algorithm (SWH2A), Sliding Window Hourly Seasonal ARIMA Algorithm (SWHSA), Sliding Window Daily Profile ARIMA Algorithm (SWDP2A) and Window Daily Profile Seasonal ARIMA Algorithm (SWDPSA) [18]. These models indicate that the hourly prediction task does not require collecting large hourly data in the training phase of model induction and it is sufficient to use daily consumption data and aggregated hourly coefficients of daily profiles for obtaining accurate hourly predictions of electricity load [18].

ARIMA model with seasonality the optimization method becomes highly variable when fixing the AR, I, MA orders and all the seasonal AR, I and MA orders to some arbitrary numbers[15]. SARIMAX is not able to react fast enough to rapid load changes that differ from the historical pattern heading to a larger forecast error [22].

The ARIMA model is described as ARIMA(p,d,q) which outlines the order of the autoregressive components, the number of differencing operators and highest order of moving average term to forecast how much future electricity is needed [11].

3.5. Artificial Neural Network

Artificial Neural Network (ANNs) is an information processing system that is motivated by the way biological nervous systems process the information. ANNs have the ability to approximate any continuous function using learning algorithms by creating internal illustrations and thus there is no need for explicit mathematical models to represent the input-output relationship. ANNs are widely used for forecasting with high precision.

Daily basis Load forecasting based on multilayer Feed Forward Neural Network using data gathered from Smart Meter was proposed in [12].Observation of two Deep Neural Network and Machine Learning approaches were discussed for short-term load forecasting [14]. DNN architectures largely outperform the traditional procedures, but DNNs require much more time to run and thus there is a tradeoff [14]. Recurrent Neural Networks (RNNs) are fundamentally different from the traditional feed-forward neural network which are sequence-based models to establish the temporal correlations between previous information and the current circumstances [16].Authors proposed a long short-term memory LSTM recurrent neural network based aggregated load forecasting framework which worked for extremely challenging task i.e. lifestyles of the consumers will be reflected in the energy consumption [16].

Authors noted the Neural Network model based on simulated annealing algorithm has a smaller approximation error, which can be used to load forecasting [13].

OS-ELM (Online Sequential Extreme Learning Machine) is a new type of machine learning algorithm that uses the single deep layer i.e. feed-forward neural network which served to deeply mine the similarity between consumer electricity behaviors according to the requirements of load forecasting, and how to increase the forecasting accuracy on the system level according to the similarity between user behaviors.

The outcome effects of MLP Neural Network model used for 24 hours ahead short-term load forecast show that they have a good performance and understandable prediction accuracy was achieved with these models [7].

3.6. Regression Tree and Support Vector Regression

Regression Tree uses recursive partitioning which examines all possible binary splits at each level for a bunch of predictors. The best splitting point for each predictor is the point which gives the lowest sum of square errors. The overfitting of the training data for a single tree was bypassed by creating a regression tree collection using bootstrap sampling with replacement and using the mean of the ensemble predictions as the load forecast[22]. Matching the load forecasts with marked values, the average forecast error of SVR is slightly lower than regression tree and neural network when predicting the load forecasting[22].

3.7. Support Vector Machine

It is a supervised learning procedure which is characterized by the usage of kernels, an absence of local minima, and sparseness of the solution and capacity control obtained by acting on the margin, or on the number of support vectors. The results of SVM used for 24 hours ahead short-term load forecast show that they have a good performance and reasonable prediction efficiency was achieved with these models [7].SVM based on the suggested data structure can perform good prediction with least error and acceptable accuracy [7].

4. Conclusion

It is a supervised learning procedure which is characterized by the usage of kernels, an absence of local minima, and sparseness of the solution and capacity control obtained by acting on the margin, or on the number of support vectors. Various ANNs types are widely used for forecasting with high precision. The results of SVM used for 24 hours ahead short-term load forecast show that they have a good performance and reasonable prediction efficiency was achieved with these models [7].SVM based on the recommended data structure can perform good prediction with least error and acceptable accuracy [7].

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