A STUDY ON PATTERN DISCOVERY OF SMART METER DATA FOR ENERGY EFFICIENCY

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***Abstract**: Infinite massive amount of data are being generated from smart meters. Precious information can be obtained by analyzing these data for efficient use of energy. Data mining algorithms are extensively used for extracting these valuable information. Researchers have been focusing on developing energy management solutions for a cleaner environment. Recognizing residents behavior and provisioning a feedback continuously about their usage is one of the effective ways to save energy in residential sector. It is assumed that the more they know and understand their consumption, the more they can track their behavior and save energy. This paper presents a study on the recent research covered for understanding behavior of household energy consumption using pattern mining algorithms as well as applications developed for reducing energy consumption and achieving a much better and efficient use of energy. The pattern discovery techniques applied during the recent 5 years are also presented.*

***Keywords**: Smart Grid, Smart Meters, Pattern Mining, Smart Home, Energy Management.*

***ACM Classification Keywords**: Smart Grid, Smart Metering.*

Introduction

WITH the evolution of new technologies, energy demand is increasing expeditiously. According to the US energy information administration annual report for 2017, residential and commercial sectors are contributing by 40% of the total power in US [EIA, Online]. Mining consumption data at increased level of granularity has attracted the keen interest of industrial and governmental sectors. Governments such as Australia, Canada, Europe, Korea, Ireland, Japan, UK and USA are investing in smart meters deployment although it is very costly and requires huge IT and communication infrastructure [Smart Grid, Online]. Smart meters are considered as a key component for initializing smart grid environment. Smart grid [Hassan, Radman, 2010] is a network of utilities, smart meters, transmission lines and power plants integrated together. The grid is called smart for being able to communicate in bidirectional way and making real time decisions. The current power electric grid is facing a lot of challenges and the smart grid, considered as its next generation, has emerged for tackling these challenges such as system stress and blackouts [Fang et al, 2012].

The advent of sensors era has promoted the task of collecting appliance usage data. Each home appliance can log its usage time and consumed power to smart meters. Infinite stream of log data are being generated on frequent time intervals. For an effective use of energy and developing a better distribution of power plans, it is crucial to mine and analyze these consumption data. However, the enormous amount of data generated at a constant rate makes the mining task a very challenging one. Academic researchers are making a great effort and studies to extract all possible analyzed information from these data. It is believed that residential sector has a great impact on energy saving and understanding its behavior is one of the key factors to achieve this. Residents can adjust their behavior if they are provided with a continuous feedback about their usage. Real time notifications can get them into a deep understanding and awareness of energy saving methods. Thus, helping them to respond to Demand Response (DR) programs. DR [Siano, 2014] is the change in energy demand in response to changes in electricity price. Thereby, notifying residents to postpone operating scheduled appliances like washing machine, dishwasher and dryer during peak hours. In this regard, a great benefit could be achieved for both consumers and producers. For consumers by lowering their electricity bills and for producers by preventing system stress and supply shortage.

As far to our study, researchers observe that consumption data follows a frequent pattern to some extent. Revealing that most of the residents follow a daily routine in their lives which is reflected on the appliances usage behavior. For example, the alarm is on and waking up at 7:00 am, taking the breakfast so coffee machine and microwave are turned on at 7:30 am. However, This daily routine can be influenced by some other factors like working days or weekends, holidays and environmental changes such as weather. The smart meter consumption log data is considered as a great data treasure where a lot of significant studies, analysis and information can be extracted to reduce energy consumption and achieve an efficient use of energy.

Data mining techniques such as clustering, prediction and pattern discovery have been applied on smart meter data to achieve energy efficiency. Clustering techniques have been very useful in promoting Demand Side Management (DSM) [Abdulaal et al, 2015]. Load profile is first extracted and then clustering algorithms are applied to group residents of similar consumption behavior together. Utility companies design demand response programs that are tailored based on residents preferences to satisfy their needed demand and gain their trust. Prediction techniques are applied to develop power distribution plans [Zeifman, 2014]. Pattern discovery techniques are applied to study appliances usage behavior of residents.

This paper is organized as follows: Section 2 covers pattern discovery techniques, then applications of smart meter data are covered in section 3, and finally conclusion and future work are derived in section 4.

Pattern Discovery Techniques

With the emergence of smart meters and the availability of such rich data, academic studies such as pattern mining, associations, prediction and clustering techniques are applied on smart meters data to achieve energy efficiency and provide a cleaner environment.

Pattern discovery, aka pattern mining, is a sub-field of data mining that intends to discover some sort of items pattern in a large dataset. Pattern discovery is very useful for studying residents behavior, extracting their preferences and predicting their actions and energy demands. This pattern could be periodic, frequent, sequential or usage pattern.

A. Periodic Pattern Mining

Periodic pattern mining discovers the occurrence of a specific pattern at constant time interval. It refers to appliance-time association. For example, the coffee machine works every day at 7 am. It is not necessary to occur at the exact time. However, it occurs in the same time interval.

Shailendra and Abdulsalam [Singh, Yassine, 2017] considered the appliance-time association as a clustering problem where appliances that operate at the same time interval will belong to the same cluster. He divides the day into 48 intervals where each interval equals to 30 minutes. He considered each interval as a cluster and developed a new algorithm that extends the k-means algorithm to cluster appliances with associated intervals.

Yi-Cheng et al. [Chen et al, 2012] also divides the day into intervals and develops Time-slot Probability Usage Pattern (TPUP) algorithm which estimates the probability that an appliance is on in a specific interval.

B. Frequent Pattern Mining

Frequent pattern mining discovers the occurrence of a specific pattern with frequency higher than a predefined threshold. It refers to appliance-appliance association where items appear together in the same time interval frequently. For example, the occurrence of printer and computer together. The main challenge in extracting frequent patterns is the reduction of search space. Hash tables data structure are used to improve performance where the key is the pattern itself and the value is its supported count.

Yi-Cheng et al. [Chen et al, 2013] introduced a new notation for representing appliances usage called usage representation. This representation is used as an initial step in developing Correlation Pattern Mining algorithm (CoPMiner). Later in [Chen et al, 2014], Yi-Cheng et al. modified the CoPMiner algorithm by including the probability concept. Then in [Chen et al, 2015], Yi-Cheng et al. developed

Dynamic Correlation Miner (DCMiner) where an incremental pattern mining is introduced. In general, pattern mining in dynamic databases is much more complex than the static ones. In the real case, smart meters log data regularly generating massive infinite amount of data. Thus, approaches are expected to mine the new logged data in real time without mining the whole database each time.

Shailendra and Abdulsalam [Singh, Yassine, 2017] extend pattern growth approach to generate Frequent Pattern tree (FP-tree). They achieve the progressive manner by mining data at the end of each day in chunks of 24-hours then updates the support count for repeated patterns.

C. Sequential Pattern Mining

Sequential pattern mining discovers the occurrence of sub-sequences items in a sequence dataset. It refers to the usage of appliances in sequence to perform specific activity. Sequential pattern mining is derived from frequent pattern mining where items sequence is considered. The word sequence implies the order of appliances usage. For example, the dryer is turned on after the washing machine. Some studies extract sequential frequent patterns where it discovers the sequence of interested frequent patterns. Ali and Ashkan [Honarvar, Sami, 2016] extracted sequential patterns using PrefixSpan extending pattern growth approach.

Marwan et al. [Hassani et al, 2015] proposed an algorithm that mines input streams without dividing them into batches. They extend Pattern Builder (PBuilder) by developing Streaming Pattern Miner (StrPMiner) algorithm to mine only one item at a time whenever it is arrived. The proposed algorithm was evaluated by comparing its performance and accuracy against SS-BE algorithm. It achieves a better accuracy but slower in performance.

In other studies, it is stated that residential activities are related to the usage of appliances where extracted information is in the form of activities instead of appliances. For example, using a microwave indicates cooking activity. Residents understand their power usage in terms of their activities. As far to our knowledge, the users have to state the activities related to each appliance by themselves as there is no automatic detection approach.

Yong et al. [Ding et al, 2015] gathered data by asking residents to submit their activities at the end of each day. SPADE algorithm is used in his approach to extract sequential activities. They found that different sequence implies different activities with different power consumption. Giving the following example S= {cooking, eating, out} implies breakfast activity while S={out, cooking, eating} implies dinner activity. Thereby, the power used in breakfast preparation is different from the power used in dinner preparation.

D. Usage Pattern Mining

Usage pattern mining discovers behavioral pattern. It aims to extract information that is useful to understand residents lifestyle and preferences which may vary with different context. The context may be temporal such as time, day and season or may be activity such as studying, cooking and watching TV. Context-based devices are appliances that are used frequently in a specific context.

Yu-Shan et al. [Liao et al, 2015] developed a framework extending Apriori algorithm for extracting context-based devices based on temporal patterns. The framework sets a power consumption constraint calculated based on previous historical usage and verify that power consumption will not exceed a certain level and if happens the system will schedule appliances based on their context-based priorities.

Sami and Nilanjan [Rollins, Banerjee, 2014] suggested annotation activity for devices usage. First, They gathered data from residents when using appliances for the first time to identify which activity this appliance belongs to. Then, they developed rule mining algorithm using JMeasure metric to extract associations between appliances and activities. Revealing that an appliance will be probably used during a specific activity. Moreover, extracting associations between appliances having common features such as an hour of a day or a day of a week. This approach can raise home residents awareness about their power usage related to activities and appliances associations.

Xinpeng et al. [Zhang et al, 2014] extracted appliances priority based on activity context. For example, the oven has higher priority than television while cooking. They gathered data by connecting every appliance to smart tap. Then, they extends Latent Dirichlet Allocation (LDA) algorithm which is used initially for text analysis to develop Activity - Power model (APmodel). The extended algorithm is used to estimate activities and appliances priority from power consumption.

Teruhisa [Miura, 2013] developed a system that controls appliances turning on/off by infrared sockets. The system logs appliances usage records with each system command. The drawback of this system is that there will be no log record if appliances are controlled from the device itself. The system aims to extract appliances priorities by calculating the frequency of turning on/off of appliances. The system is trained by users feedback through proposing recommendations for appliances controlling and then the user can agree or disagree with these recommendations.

Yi-Cheng et al. [Chen et al, 2012] developed a system where sensors are installed for each home appliance. These sensors gather usage data and send it to a cloud server every 5 seconds. Daily Behavior-based Usage Pattern (DBUP) algorithm was developed to cluster similar daily usage. The system calculates power usage for each appliance and presents analytic dashboards revealing appliances frequent usage time.

Below in table 1, a summary of pattern discovery techniques applied on smart meter data is presented.

Table 1. Pattern Discovery Techniques Summary

Technique	Authors	Objective	Algorithm	Dataset
Periodic Pattern Mining	Shailendra and Abdulsalam [Singh, Yassine, 2017]	Extracting appliance-time association	K-means extended by dynamic programming	UK-DALE [Kelly, Knottenbelt, 2015]
	Yi-Cheng et al. [Chen et al, 2012]	Extracting time slot probability usage pattern	TPUP Algorithm	Home of 6 appliances [Chen et al, 2012]
Frequent Pattern Mining	Yi-Cheng et al. [Chen et al, 2013]	Extracting associations between appliances	CoPMiner extending UPrefixSpan	REDD [Kolter, Johnson, 2011]
	Yi-Cheng et al. [Chen et al, 2014]	Extracting appliances associations probabilistically	CoPMiner extending UPrefixSpan	REDD [Kolter, Johnson, 2011]
	Yi-Cheng et al. [Chen et al, 2015]	Extracting appliances associations progressively	DCMiner extending UPrefixSpan	REDD [Kolter, Johnson, 2011]
	Shailendra and Abdulsalam [Singh, Yassine, 2017]	Extracting appliances associations progressively	FP-Growth	UK-DALE [Kelly, Knottenbelt, 2015]
Sequential Pattern Mining	Ali and Ashkan [Honarvar, Sami, 2016]	Extracting appliances sequence pattern	PrefixSpan on Spark platform	SGSC [Honarvar, Sami, 2016]
	Marwan et al. [Hassani et al, 2015]	Extracting appliances sequence pattern using batch-free approach	StrPMiner extending Pbuilder	REDD [Kolter, Johnson, 2011]
	Yong et al. [Ding et al, 2015]	Extracting appliances sequence pattern	SPADE algorithm	23 households in Japan [Ding et al, 2015]
Usage Pattern Mining	Yu-Shan et al. [Liao et al, 2015]	Extracting context-based devices based on temporal patterns	Extending apriori algorithm	Smart meter data [Liao et al, 2015]
	Sami and Nilanjan [Rollins, Banerjee, 2014]	Extracting association rules between context and device usage	Rule mining algorithm using JMeasure metric	6 households in US [Rollins, Banerjee, 2014]
	Xinpeng et al. [Zhang et al, 2014]	Extracting appliances priority	Extending LDA algorithm	14 households [Zhang et al, 2014]
	Teruhisa [Miura, 2013]	Extracting residents preferences	Learning preferences by user feedback	Home for 7 appliances [Miura, 2013]
	Yi-Cheng et al. [Chen et al, 2012]	Extracting daily behavior usage pattern	DBUP Algorithm	Home of 6 appliances [Chen et al, 2012]

From this summary table we can observe that FP-Growth, Apriori, PrefixSpan and SPADE are the mostly used algorithms for pattern mining. UK-DALE [Kelly, Knottenbelt, 2015] and REDD [Kolter, Johnson, 2011] are the mostly used datasets for developing pattern mining techniques.

Smart Meter Data Applications

Smart meter data has a great potential to develop applications that manage energy efficiently. Below are some of these applications:

- Demand response programs; energy providers are developing and designing demand response programs that are tailored based on user preferences. In such programs, it is very important to gain customers trust by respecting their preferences and without lowering their level of comfort. Clustering techniques are applied to group similar residents with similar load profiles together. Demand response programs are developed for each cluster to guide residents in this cluster for an effective use of energy, i.e. changing in their demand in response to changes in electricity price [Vardakas et al, 2015].
- Integrating with renewable energy resources; with the rapid increase in energy demand, it is essential to find other renewable and clean energy resources such as solar panels and windmills. With the benefit of bidirectional communication of smart grids, the excess demand can be transmitted to other areas having shortage in power supply [Bhalshankar, Thorat, 2016].
- Billing system; the transmission of real time data can be used to develop a billing system. Since the smart meter sends these data every predefined time interval, the readings are obtained in an updated manner instead of a meter reader that passes by and takes the readings every month. In addition to, developing an analytical tool for home residents by which they can view their bills in an itemized form [Weiss et al, 2012]. This tool is supposed to get them into deep understanding about the amount of energy used for each appliance and the cost corresponding to this usage.
- Prediction; energy providers are paying much attention to reach a good accuracy of predictive models. It is very important to have a future estimate about the needed demand in each area. In case of any failure, power redistribution decisions can be easily taken if there is a predicted demand in each region [Zeifman, 2014].
- Utilities applications; with the availability of smart meter data in real time, several applications can be developed such as decision making, network monitoring, power distribution, risks reduction, faults detection and handling [Wang et al, 2018].
- Estimating household characteristics; smart meters data are not only used to save energy but also can be used to reveal social characteristics such as estimating number of appliances in a home and the standard of living [Beckel et al, 2014]. This information can be used for any socio-economic statistics.
- Home Energy Management System (HEMS); it is a system connecting home appliances and smart meter together through home area network [Niyato et al, 2011]. HEMS is responsible for

visualizing appliances consumption in real time and controlling appliances remotely. In addition to, notifying residents about any abnormal usage or responding to demand response programs if needed.

- Recommendation systems; recommending to residents methods to save energy. For example, when a resident operates scheduled appliances like washing machine at peak time, a notification is send to the resident suggesting another time to operate this appliance. Some recommendation systems learns from user feedback. Daniel et al. [Schweizer et al, 2015] propose a recommendation system that is trained from user feedback. The system asks the user for each recommendation whether it was useful or not.
- Theft detection; pattern discovery techniques are applied to study the behavior of residents. Electricity theft crimes could be detected when any abnormal usage is noticed [Sahoo et al, 2015].

Conclusion and Future Work

This paper presents a study on the techniques proposed to achieve energy efficiency in residential sector. Our study focuses on pattern mining methods applied to discover periodic, frequent, sequential and usage patterns. Periodic patterns discover appliance-time association. Frequent patterns discover appliance-appliance association. Sequential patterns discover sequence of appliances usage and finally usage patterns discover appliances priority related to context-based. As far to our study, we observe that FP-Growth and Apriori algorithms are mostly used when mining frequent patterns while PrefixSpan and SPADE are mostly used when mining sequential patterns.

Key challenges are still observed when mining smart meter data and developing solutions are needed to tackle these challenges. Massive infinite streams of data are being generated from smart meters. It is impossible to mine the whole database whenever a new record is generated so an incremental progressive approach should be used instead. Moreover, studies are applied on the hypothesis that residents behavior follow some sort of usage pattern and it is reflected on appliances usage but this behavior can be changed easily with time. For example, the air conditioner is extensively used in summer and not used at all in winter. Also, some patterns may be obsolete at any time and new patterns may need to be detected. Thus, an automatic fast learner approach is needed to detect these behavioral changes, learn and extract new mined data. In our future work, we will develop an incremental progressive pattern discovery method considering temporal changes and focusing on performance enhancement. In addition to, considering residents feedback about analyzed usage data and its effectiveness for saving energy.

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