Internet of Things (IoT) and Smart Technologies: Framework of Temporal Data Mining Concerning Smart Meter

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Abstract

This paper attempts to propose a framework to study the adoption pattern of smart electrical technologies based on the existing understanding of technology adoption. The main thrust of this research is to develop a framework that may become practical right away,on availability of data from these technologies. In the absence of existing data, this paper generates the data with the help of computer simulation, and shows how wealth and technology diffusion theories can be explored for developing the proposed technology adoption framework. It is argued that results based on the proposed framework are able to identify the trends and association in the adoption of these technologies within society.

Keywords: IoT, technology adoption, temporal data mining, smart meter, smart grid, smart home, smart devices

1. Introduction

This paper proposes a framework to mine probable and feasible business solutions from the enormous data generated from Internet of Things (IoT) devices. Smart meters are one such device which may be categorised as initial examples of IoT's that may soon become an integral part of households (Depuru, Wang, Devabhaktuni, & Gudi, 2011; Greveler, Glosekotter, Justus, & Loehr, 2012). Smart meters are capable of transferring electrical consumption metering details of a household on real time basis to electricity provider. Furthermore, this meter can also transfer equipment wise recording of the consumption pattern, in case the house is equipped with smart devices. Due to this capability of the smart meter, adoption time of various smart electrical devices installed in a residence can be recorded very easily (Nezhad, Wijaya, Vasirani, & Aberer, 2014). This recording, if mined following data mining techniques, may provide various useful adoption patterns that remain unknown otherwise. Current electric meter does not offer this facility of observing and recording electricity consumption of different electrical devices. The importance of this research becomes evident since electric meters are part of every household numbering thousands of millions in number. Moreover, every house is equipped with several electrical devices.

The proposed topic becomes more important due to three reasons. First, IoT's are the future of the world. Second, IoT's will generate huge amount of data, the use of which is not thought of at present. Third, there is no prior research work on a similar topic. Examples of IoT's i.e., smart meter and smart devices, are to become common in the event of the present electric meter being replaced for effectiveness and efficiency.The data generated by the combination (smart meter and smart devices)will be enormous in size. This data will have record of all the operations of all the devices on 24*7*365 basis. The size of the data will be huge;conventional analytical techniques cannot handle it. Therefore, this data offers a unique opportunity to data scientists to explore techniques that may be of help to the various stakeholders involved. An example of such trends is, mining the adoption pattern of various smart electrical devices within the household. Mining these patterns will not only be of help to equipment manufacturers to understand their customers better, but also to policy makers to frame suitable policies in alignment with their long term socio-environmental objectives.

2. Literature Review

Literature review section is organized in three sub sections. First section explains the overview of data mining literature relevant to our research. Second explains the apparent research gap in the reviewed literature of data mining and the third generates research questions to be addressed based on these gaps. Data mining literature specifically focused to time trend is of interest for our research. The first mention of such an idea was observed in 1998 in a paper titled "The intelligent interface for online electronic medical records using temporal data mining" by Spenceley & Warren(1998). Since then two prominent fields have been extensively usingtemporal data mining; one, medical (Bellazzi, Larizza, Magni, & Bellazzi, 2005; Eriksson, Werge, Jensen, & Brunak, 2014; Svanstrm, Callrus, & Hviid, 2010)and another, geographic information system and urban planning(An, Zhang, Zhang, & Wang, 2014; Cheng & Wang, 2008; Kitamoto, 2002).

Besides medical and urban planning fields, research of temporal data mining is also emerging in the context of smart environment, specifically for smart homes. One research following this technique of data mining in the context of smart homes is by Cook & Jakkula, (2008). This paper uses the technique of temporal data mining for the detection of anomalies in smart homes. These anomalies are events happening within continuously observed environment that are other than day to day routine, may be accident, fire etc. Possibility of detection of such anomaly becomes possible because smart homes are residences equipped with smart devices capable of sensing the environment. Furthermore, these smart devices, in the presence of other smart technology, sequentially connect to smart meter and smart grid. So smart devices, smart home, smart meter and smart grid form interlinked chains. Combining these separate segments of the chain together results in smart environment. Out of these four sub units of smart environment, smart grid is the subject relatively more studied in research. There are quite a few papers which study application of temporal data mining in the context of smart grid (Fan, Chen, Kalogridis, Tan, & Kaleshi, 2012; Prasad & Avinash, 2013; Samantaray, 2015).

Literature review of temporal data mining clearly demonstrates that, in comparison to the field of data mining, this area is very new. Furthermore, there are relatively limited efforts by researchers to explore the field of temporal data mining. Therefore, there are very few papers pertaining to this research subject. Out of a limited number of 114 papers used for literature review, majority of efforts are presented as conference papers; publication as journal articles is limited. As a result, there are very few papers on the application of temporal data mining in smart homes(i.e. Cook & Jakkula, 2008; Jakkula & Cook, 2011). Very limited number of papers (e.g. Chou, Hsu, & Lin, 2014; Zhang, Grijalva, & Reno, 2014) and the anticipated extensive application of smart meter in future, suggest a gap in existing research efforts. Hence investigation and future research in this field is desirable. Considering the evident gap in literature, this paper aims to bridge this to an extent. The present effort of bridging the gap may be of concern to certain stakeholders of smart meters. Users, manufactures, electricity providers and policy makers within the government are few important stakeholders. Out of these, manufactures of smart devices would be the first to be concerned. Manufactures would be interested to know the adoption pattern prevailing in society. The prediction of this adoption pattern will provide a fair idea to manufactures to appropriately plan their business strategy. There are innumerable electrical devices in households at present and more or less, all are set to become smart in due course of time. A study of adoption patterns in the early stage will give added advantage to manufactures to invest on innovation and design of the appropriate product and plan its marketing accordingly. Considering these implications, this articles aims to design a framework that may suggest answers of the following questions, related to manufacturers of smart devices.

1. What are the characteristics of households that adopt a particular smart device at particular time reference? User's demographic and social characteristics can be concluded, based on his electricity consumption detail (Newing, Anderson, Bahaj, & James, 2015). These characteristics are the number of occupants, presence of children, type and size of dwelling, and socio-

economic and geo-demographic characteristics of the household(Newing, Anderson, Bahaj, & James, 2015). For the purpose of simplification, this paper does not simulate the variation in power consumption of the single household. Rather only the total amount of yearly consumption is modelled. Therefore, it is not possible to mine all the possible household characteristics with the present data. But the economic aspect, significantly associated with the amount of electricity consumption, is considered as the variable for consumer segmentation. By integrating electricity consumption of the single household at the time of device adoption will help to know the present segment of customers that adopt devices. Furthermore, it gives an indication of the next appropriate consumer segment based on which customized business plan for that section can be prepared.

2. What is the sequential adoption pattern between two particular smart devices? With this analysis manufactures may prepare for the production and marketing of the next product analyzed to be adopted by the customer segment.
3. What is the average time lag between adoptions of two particular smart devices? Knowing the time of adoption by society will give opportunity to firms to strategically plan their future products.

Remaining part of the paper is organised as follows. Next section, Section 3, describes smart meter and related technologies. Section 4 elaborates the concept of temporal data mining and its evolution. Section 5 defines the nature of temporal data availability, and Section 6 defines the problem and explains the tentative solution which temporal data mining may offer. The final section, Section 7, deals with conclusions of the paper and suggests future work to be done in this regard.

3. Smart Meter and Related Smart Technologies

In the context of electronics, smart is defined as any method or device having both sensing and control capabilities (Baz, 1996). In accordance with this definition all the smart devices are capable of sensing the surrounding environment and are able to accordingly guide and control their functions. For example, smart bulb will be capable of sensing the surrounding illumination level and presence of human being. Based on this informationthe smart bulb will be able to decide whether to light itself up or not. In the context of IT, definition of smart is slightly modified; besides sensing and controlling capabilities, communication to other devices and networks is also required. This capability defines smart devices as"personal devices interacting with users, sensing their environment, and communicating with each other" (Allwright et al., 2006). Smart meters are also an example of smart devices to be deployed in future households. As defined, smart meters too are capable of sensing the electric consumption in totality, as well as partially by smart devices of the home. Smart meters may force control on consumption of electrical devices, if programmed. Smart meters are also capable of communicating this consumption data through internet to the electricity provider on near real time basis.Therefore, smart meter reaches its full capability only in the presence of smart electrical devices and in their absence offers only limited functionality. Smart grid, as one of the associated technologies, is explained below.

3.1 Smart Grid

Smart grid is defined as "the electricity grid that uses digital technology to improve reliability, security and efficiency of the electric system, from large generation, through the delivery systems to electricity consumers and a growing number of distributed generation and storage resources"(Li, Zhou, & China 2011, p.99). Definition of smart grid makes it clear that smart grid uses computer technology to integrate all parts of electricity distribution and consumption intelligently. The principle objective of this integration is to make the system more efficient. Efficiency of the smart grid is the result of availability of all consumption records in the process of electricity distribution via smart grid. Through digital technology smart grid automatically keeps the travel and consumption records of electricity, from generation till the last point of consumption. Because of its digital nature smart grid is not only capable of keeping all the data recorded in the process of electricity distribution, but it can also communicate this data to various stakeholders and help them take proper decisions at the appropriate time. Present electricity distribution lacks this capability and hence is susceptible to several problems. The biggest problem of present day electricity transmission is energy and power shortage, power outage and electricity theft. To an extent these problems can be resolved with the help of smart grids (Seetharam et al., 2013). Smart grid offers unique solutions, which are unimaginable in present context, to these problems. Differential pricing to resolve energy shortage at peak hours and accurate data availability of power outages and theft detection are a few of them. The fully functional smart grid system does not mean just the presence of smart grid and smart meter; smart electricity devices are other essentials required to attain the full capability offered by smart grids. If smart grid is an essential requirement beside smart meter at one end, then smart electrical devices are essential at the other end.

3.2 Smart Devices

By embedding microelectronics devices to any every-day object, it can be converted into a smart object (Mattern, 2003). These smart objects or devices can communicate by wireless means and they may form networks that may rise to a world-wide distributed system network of magnitude much larger than today's Internet (Mattern, 2003). Recentdevelopments in sensor technology has made sensors capable of detecting various environmental phenomena, including but not limited to, light, acceleration, temperature etc. Radio sensors are another interesting development in this area;they can report their observations without any energy supply within a few meters distance. These sensors obtain the required energy from the environment or directly from the measuring process itself. The capability of remote control, security alarm and sensors are utilized while converting an ordinary home into smart home with the application of these smart devices (Kadam, Mahamuni, & Parikh, 2015). An overview of smart meter, smart grid and smart devices helps us in understanding the concept of smart home and smart environment in which smart devices, in interaction with smart meter and smart grid,produce enormous amount of data. The present world has not witnessed data of such nature and quantum, and hence the potential capability and threats posed by this data availability is still unknown. However, certain characteristics of this data may be visualized. Based on the use of smart devices, smart meters will keep recording the use with time stamp on it. Time stamping on the data from various devices puts it in the category of temporal data. Analysis of this data comes under the specialised area of data mining, known as temporal data mining. Temporal data mining may offer certain usability to this data for pattern mining, useful to stakeholders.

4. Temporal Data Mining

The previous section discussed the integration of smart meter and smart devices to produce enormous amounts of data.It is nearly impossible to handle this data without the intervention of data mining. Data produced by smart meters are of enormous volume and high velocity (Nezhad et al., 2014). Being temporal in nature, temporal data mining techniques offer better analysis of data compared to that of traditional data mining. Temporal data mining is an extension of traditional data mining. Application of temporal data mining lies in mining the sequence of activities rather than just cross sectional states of it, and thus, they offer better inferences than that of traditional data mining (Camara, Naguingar, & Bah, 2015). These inferences may result in contextual and temporal proximity of two or more subjects of study, some of which may indicate cause and effect relationship between multiple series of data (Camara et al., 2015).

5. Nature of Data

Smart devices installed in smart homes are comprised of hardware and software, with time stamping of its use recorded in a server (Mohassel, Fung, Mohammadi, & Raahemifar, 2014). Smart meters communicate consumption data equipped with time stamping to both the user and the service provider (Mohassel et al., 2014). For the purpose of this research adoption of such devices by society is assumed to be similar to other technology adoption seen historically. We further assume that once adopted by households (first time stamp recorded in the data server), the device is used on a regular basis. Cases of abandonment after adoption are not taken into account. Present study is concerned only with the first time record of use of any new device by the consumer. Some of the information anticipated to be obtained from smart environment and used to answer the formulated research questions are:

Id<- is consumer identity

con<- per year electricity consumption by consumer

t1<- is first time in the electric meter device number one is recorded

t2<- is first time in the electric meter device number two is recorded

tm<- is first time in the electric meter device number m is recorded

The combination of this information will generate m+2 tupple data. The vector form of this data will be of <Id, con, t1, t2,…………tm> type.

6. Problem Definition

Smart meter are still uncommon in most of the underdeveloped and developing countries (Weranga, Kumarawadu, & Chandima, 2015). But the process of smart metering has started in the developed world. In Sweden and Italy most of the households have already adopted smart meter (Wehlitz, Werner, & Franczyk, 2014). In the Indian context, in the absence of deployed smart meters, data depicting consumption pattern of smart devices is not available. Considering this difficulty the data of adoption is generated through simulation. 1000 data points are generated in the R-studio statistical software. Generation of data is in the format explained in Section 5 and is supported by literature. Individual record of this data has consumption of electricity as one item and adoption times of various smart devices as the rest. In literature it has been statistically proved that electricity consumption is significantly related to the level of income of family (Francisco, Aranha, Zambaldi, & Goldszmidt, 2006). Furthermore, in many researches income is found to follow the pareto distribution (e.g. Dagsvik, Jia, Vatne, & Zhu, 2013; Persky, 1992). Therefore, following these two premises, hypothetical data in R software is generated using pareto distribution. Pareto distribution is also known as power law distribution. In pareto distribution the frequency of observation is inversely proportional to the amount of consumption. If amount is more, frequency or probability of its occurrence will be less and vice averse. Based on average per capita electricity consumption in India as 800KWH (Chauhan & Saini, 2015; Sharma & Balachandra, 2015), variation in consumer per capita consumption is modelled with maximum yearly consumption of electricity as 12000 KWH and 100 KWH as minimum electricity consumption. Modelling of electricity consumption is followed by modelling the time pattern of smart device adoption. Rogers' diffusion of innovation (DOI) theory explains that adoption of any innovation in society follows a normal curve in time (Sahin, 2006). Innovators are the first segment of society to adopt these products, followed by early adopter. After these segments of society have adopted the product, it is adopted by early majority and late majority segments. In the end, the population characterised as laggards adopt it (Sahin, 2006). Therefore, to simulate adoption data in time, normal distribution is used. It is assumed that smart device adoption will take approximately 10 years (3650 days). Therefore the last person of the proposed 1000 people will adopt it after nearly 10 years from the first person. It has been found that there is a high degree of correlation between economic status of the individual and adoption of innovation (Al-Ghaith, Sanzogni, & Sandhu, 2010). This fact is used in simulation of data. As a result, multivariate data is generated following two distribution patterns, pareto and normal. Since there is correlation between the amount of electricity consumption by a household and adoption of smart devices, certain degree of correlation is maintained between these two in data generation.

Based on the data simulated and following the proposed framework in Figure1, the timeline of adoption of various smart devices by an individual customer can be generated. We use these schedules of adoption for temporal association mining of different devices. For the purpose of explanation the schedule of adoption of four devices by three customers are shown below:

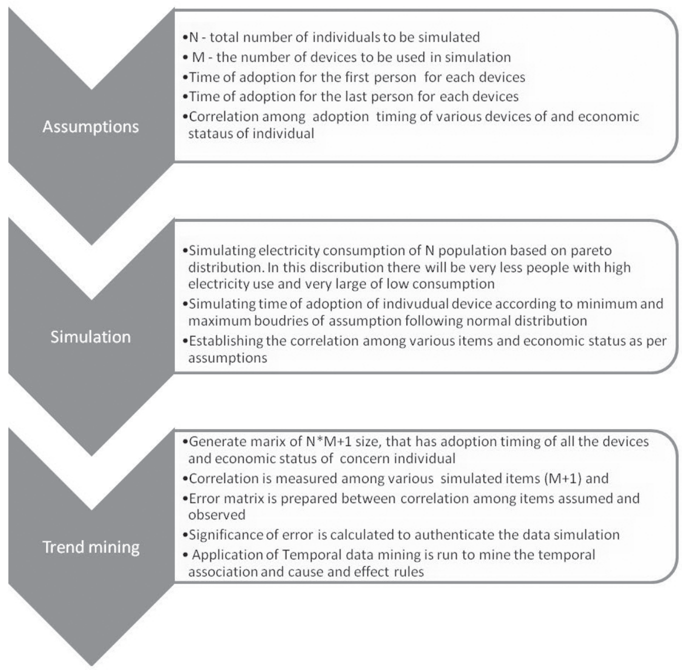

Figure 1- Framework of Adoption Trend Mining Data

Figures 3, 4 and 5 represent the time of adoption of four smart devices on the timeline by three customers. We can mine the temporal association of adoption of various devices based on this information. For example, the association of adoption of device 2 followed by 1 is 2/ 3 i.e. 67%. For customers1 and 3, device2 is adopted immediately after device 1. Similarly, device 1 selected after any other device is 0%.

Figure 2- Adoption timing of four devices (Customer-01)

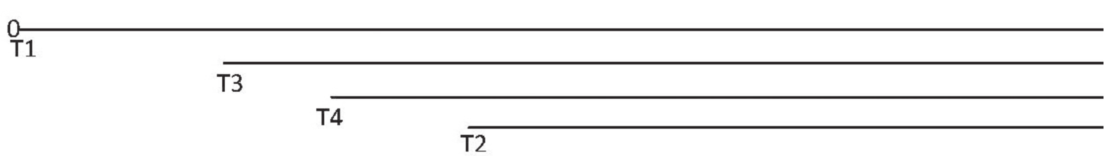

Figure 3-Adoption timing of four devices (Customer-02)

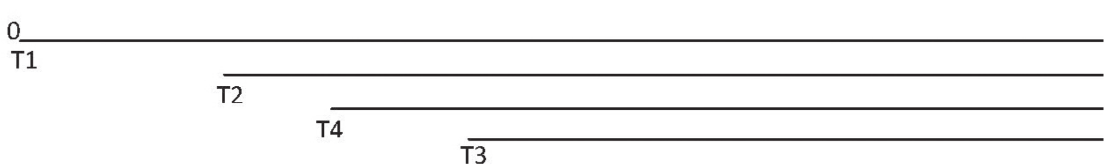

Figure 4-Adoption timing of four devices (Customer-03)

7. Conclusion and Future Work

Once smart meters are part of society huge data will be generated with the potential to mine useful insights, not only for manufacturers of smart devices, owners of electricity supply, government for policy formation, but also to the owners of the houses consuming electricity, to bring the consumption to more efficient and economical levels. The nature of data obtained from this process is big is size in comparison to the data available from say, retail stores. The number of consumers,in case of retail stores,is mostly in thousands whereas the consumers of smart meter will be millions in size. The complexity of the data is also much more compared to retail data. Retail data is mostly cross sectional in nature whereas smart meter data has time as another component. For simplification this study only uncovers one aspect of the problem, adoption mining of the smart devices in a home. There are several other further complex mining activities that can be performed with the same data. We presume that this field will mature in due course of time and researchers in future will bridge dimensions not touched in the present paper.

There are four major stakeholders for this study. First, manufactures of smart devices who are concerned with the marketing of their product. Second, electricity distributing companies whose main concern is the elimination of existing problems associated with the distribution of electricity, especially in developing countries. Third, the government or policy makers who are enabled and are in a position to formulate appropriate policy; policy that is not only capable of eradicating existing problems of electricity generation, distribution and consumption, but is also acceptable by society. Fourth, consumers of electricity, who, in present scenario, are totally unaware of their own segregated and detailed electricity consumption. This awareness may help them to take appropriate electricity consumption decisions to optimize the level of consumption. This paper mainly focuses on manufactures of smart devices as its subject of concern. This study will help manufacturers of smart devices to know adoption patterns and understand the consumer's segment. This understanding will help them to better formulate their marketing strategy. Furthermore, the proposed study will help the manufacturers in two ways. First, it will mine the profiles of customers as initial adopters of their product. Second, this study will mine the association pattern between two or more launched products. Understanding of the temporal association between devices will let the manufacture know the average time lag between the adoptions of these devices. This information will guide future manufacturing and marketing strategy of the product.

Present study explains a very limited potential use of the data available from smart meters. Data simulation done for this study is also very simplistic. That is only good enough to explain a few applications. Research has found that electricity consumption variations, daily and seasonal, are capable of giving insights about the demographic and social details of households. In the present attempt, we have not covered these aspects of smart meter data mining. In the next attempt, we propose to integrate this complexity. Furthermore, in the next step of the study we aim to propose an algorithm to get insights from the simulated data.

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