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From Smart Meter Data to Pricing Intelligence: Real Time BI for Business Innovation

Turku Centre for Computer Science

TUCS Technical Report
No 1035, February 2012

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Abstract

The deployment of smart metering in the electricity industry has opened up the opportunity for real-time BI-enabled innovative business applications, such as demand response. Taking a holistic view of BI, this study introduced a visual data mining driven application in order to exemplify the potentials of real-time BI to the electricity businesses. The empirical findings indicate that such an application is capable of extracting actionable insights about customer's electricity consumption patterns, which will lead to turn timely measured data into pricing intelligence. Based on the findings, we proposed a real-time BI framework, and discussed how it will facilitate the formulation of strategic initiatives for transforming the electricity utility towards sustainable growth. Our research is conducted by following the relevance-rigor-design cycle iterations in the design science research paradigm. By addressing an emerging issue in the problem domain, it adds empirical knowledge to the BI research landscape.

Keywords: Business intelligence, visual data mining, business innovation, design science research, electricity consumption profiling, self-organizing maps.

TUCS Laboratory
Data Mining and Knowledge Management

1. MOTIVATION AND AIM

In the decision support domain, business intelligence (BI) has evolved as an important field of IS research over the past decade. Meanwhile, in the world of practice, BI has been recognized as a strategic initiative and a key enabler for driving business effectiveness and innovations. For instance, BI has been ranked as the top 1 technology priority by CIOs from 2006-2009 and within the top 5 for 2010-2011, according to Gartner surveys. BI, as defined in Wixom and Watson (2010), is an umbrella term to describe applications, technologies, and processes for gathering, storing, accessing, and analyzing data to help business users make better decisions. BI involves database management (DBMS) and data warehousing, usually classified as 'getting data in' on the one hand; and enterprise reporting, online analytical processing (OLAP), querying, business performance management (BPM), data mining, complex event processing, etc., as 'getting data out' on the other (Watson and Wixom, 2007). It is widely acknowledged that 'getting data in' delivers limited value to an organization, in terms of performance improvement, decision making support, and innovation creation. In other words, BI is not only concerning establishing IT-enabled enterprise infrastructure; moreover, it is aiming to facilitate business innovation and to transform an organization towards sustainable profitable growth.

This issue is particularly relevant in the European electricity industry today. The ongoing implementation of smart metering (i.e., remotely-readable, two-way communication, automated meter reading system, AMR) is presenting both opportunities and challenges to the electricity utilities, with regard to how to manage and fully utilized such a wealth of hourly or half-hourly measured data. In particular, how to integrate smart meter data into legacy enterprise data warehouse systems and turn near real-time data into market intelligence for business innovation is crucial for the overall success of AMR investments.

In this study we propose a holistic real-time BI approach for the electricity utilities to take into account in their effort to develop a customer-centric demand response retail market. We will introduce a visual data mining driven application to exemplify this BI approach. The research questions are: (1) what actionable insights can this visual data mining based analytical application offer, and (2) how can such a real-time BI approach contribute to pricing differentiation and/or business innovation with respect to facilitating an organization to sustainable growth?

The paper is organized as follows: the next section will present related research and the research background. In section 3, the research method and research design will be described. The data mining model will be introduced in Section 4, while Section 5 will contain the results. The implications will be discussed in Section 6. In the final part of this paper, the conclusion will be drawn and future research will be addressed.

2. RELATED RESEARCH AND BACKGROUND

2.1. Business Intelligence

Since it entered into academia's vocabulary, BI as a research subject has been extensively studied in the IS discipline. Jourdan et al. (2008) analyzed 167 articles with BI related topics in ten leading IS journals published from 1997-2006. They identified five relatively distinct BI research categories and classified nine BI research methodologies during the 10-year period. Recently, Maghrabi et al. (2011), Saldanha and Krishnan (2011), and Marjanovic and Roose (2011) examined the strategic and operational role of BI in service innovation, product and service development, and business process improvement, respectively. Watson (2009), Wixom and Watson (2010) proposed the concept of *BI-based organizations* because of the increasing role of BI played in the enterprise's operations and overall business success, as seen in Harrah's Entertainment and Continental Airlines. These studies have shown BI capabilities of supporting problem and opportunity identification, decision making, and alignment of operations with corporate strategy, thus contributing to the enterprise's competitiveness and sustainable development (March and Hevner, 2007; Olbrich, Poeppelbuss and Niehaves, 2011).

Today's growing competitive pressure in business has led to increased needs for real-time analytics, i.e., so called real-time BI or operational BI (Chaudhuri, Dayal and Narasayys, 2011; Watson, 2009). The value of real-time BI is to reduce the latency between business events and when the operational data is captured (Data Latency), and when the event data has been analyzed and the findings are available for use (Analysis Latency), and when action has been taken (Decision Latency); so as to increase the responsiveness of the organization to varying customer needs and ever-changing market situations (Hackathorn, 2004). It is especially true with respect to the electricity production, transmission, and retail businesses due to the characteristics of electricity--which is non-economically-stockable and the demand-supply needs to be constantly in balance. Therefore, the focus of this study is to present a real-time BI framework for the electricity business.

2.2. Smart Metering and Demand Response

The deployment of AMR to both commercial and household customers in the European electricity industry has opened up the possibility for real-time BI-enabled innovative business applications, such as demand response. Demand response refers to "*the changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time. Further, demand response can also be defined as the incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized. Demand response includes all intentional modifications to consumption patterns of electricity of end-use customers that are intended to alter the timing, level of instantaneous demand, or the total electricity consumption.*"(Albadi and El-Saadany, 2007).

So far, studies regarding the utilization of AMR data have mainly focused either on cost-saving from manual customer meter reading (Cotti and Millan, 2011), or on how to enhance electricity distribution operations such as automated fault detection and healing (Garpetun, 2011), improving the accuracy of load modelling (Mutanen, Repo and Järventausta, 2011), and AMR-based short-term load forecasting (Abdel-Aal, 2004; Valtonen, Honkapuro and Partanen, 2010). As a CEER (Council of European Energy Regulators) survey (2011) pointed out, among the three European countries (i.e., Italy, Sweden, and Finland) that have made decision to roll out smart meters, none have a demand response scheme based on smart metering. Yet few empirical studies can be found concerning a holistic BI approach based upon real-time smart meter data. In this paper, we will address this issue through demonstrating a visual data mining driven BI application.

3. METHODOLOGIES

3.1. Research Method

This research is based on the design science research paradigm in the IS field (Hevner, March, Park and Ram, 2004; Hevner, 2007; March and Smith, 1995; Nunamaker, Chen and Purdin, 1990; Walls, Widmeyer and Sawy, 1992). Essentially, design science research is a solution-oriented and prescription-driven paradigm (van Aken, 2004), which aims at contributing to the knowledge body of IS practice and research via constructing novelty and utility combined IT artifacts (March and Storey, 2008). The design artifact is to serve identified business opportunities (Iivari, 2007) and/or provide solutions to management problems (Gregor and Jones, 2007). In this study, we follow the design science research framework proposed by Hevner (2007) to guide our research design.

This research is conducted by following the three cycle iterations, as depicted in Figure 1. It is initiated by recognizing the business opportunity which is enabled by the implementation of AMR in the application domain of electricity industry, i.e., started from the *relevance cycle*. Accordingly, we came to the *rigor cycle* through reviewing BI topic related IS literature, empirical studies in the application domain (as presented in the previous section), and both theoretical and application-oriented literature regarding data mining technique (as seen in the following part of this section). The existing knowledge formed the scientific foundation for us to build the data mining model and the real-time BI framework in the *design cycle*. Specifically, the model building follows the work flow, as shown in Figure 2. The goal of the data mining model is to profile the customers according to their actual electricity usage, and thus to gain better understanding and insights into the customers' consumption patterns in order to guide dynamic pricing in the demand response scenario. The rest of the model building steps from data collection to model selection are described in Section 4. During model building, the technical evaluation is performed, as presented in Section 4. The field testing is planned for the future research. The use of the model and the implication of the real-time BI framework are discussed in Section 6.

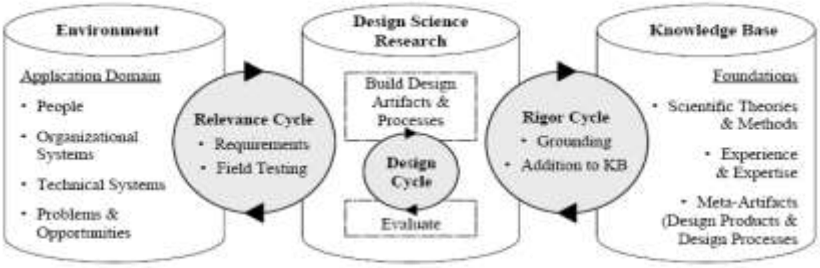

Figure1. Design Science Research Cycles (adopted from Hevner, 2007)

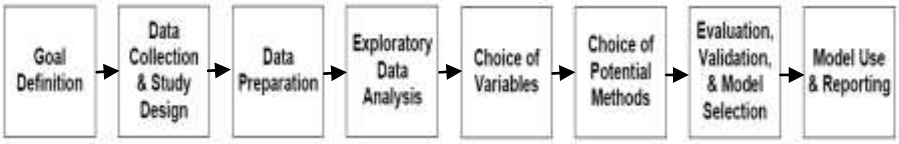

Figure2. The Steps of Model Building in the Design Cycle (adopted from Shmeuli and Koppius, 2011)

3.2. The Visual Data Mining Tool

In this study the Self-Organising Map (SOM) is used for the purpose of visual data mining. The SOM is a data mining method based upon Artificial Neural Networks. It is a widely used unsupervised neural network, particularly suitable for clustering and visualisation tasks (Han and Kamber, 2000). The SOM is capable of projecting the relationships between high-dimensional data onto a two-dimensional display, where similar inputs are located close to each other. By adopting an unsupervised learning paradigm, the SOM conducts clustering tasks in a completely data-driven way, i.e., no target outputs are required (Kohonen, 1997). Because of its robustness, it requires little *a priori* knowledge concerning the input data, and is more tolerant to difficult data, including non-normal distributions, noise, and outliers, than conventional statistical tools. In addition, the SOM's ability to preserve the topological relationships of the input data and its excellent visualisation features motivated the authors to apply it in this study. The SOM has been applied as an analytical tool in finance, medicine, and engineering applications (Deboeck and Kohonen, 1998; Kaski, Kangas and Kohonen, 1998; Oja, Kaski and Kohonen, 2002). The SOM has also been used in the energy sector for e.g., power system stability assessment, online provision control, load forecasting, as well as electricity distribution regulation and benchmarking (Lendasse, Lee, Wertz and Verleysen, 2002; Nababhushana, Veeramanju and Shivanna, 1998; Rehtanz, 1999). For a thorough discussion of the SOM algorithm, we refer readers to Kohonen (2001) for details.

4. THE DATA MINING MODEL

The data used for building the data mining model is from a Finnish utility's operational systems, including AMR data in 2009 and customer statistics. The data from the AMR system includes Meter ID, Electricity Usage, Reading Time, Peak Load, and Peak Time. And the customer statistics consist of Electricity Rate, Housing Type, Consumption Category, Fuse Type, etc. For each meter, the electricity usage is registered in 27 hours 20 minutes time intervals, due to the AMR and communication technology adopted. Even though the AMR data are not hourly measured, they are adequate for studying customers' electricity consumption patterns in terms of day-of-the-week, seasonal, and time band effects[1].

In the data preparation phase, a great deal of data pre-processing work, including data integration, transformation, aggregation, and normalisation, has to be performed to create customer signatures, with one record per customer and a range of variables capturing customers' demographic and consumption related features. We excluded the customers whose records included less than one year, or whose annual consumption is 0 kWh. There are in total 11,964 customers included in this study.

The variables used fall into two types based upon their purpose – one type is for describing the customer's general consumption and demographic profile, and the other is for investigating customers' weekday-weekend, seasonal, and time-band related consumption patterns. The variables are described in Table1.

Variables	**Description**
Average Consumption (kWh)	the customer's average consumption per 27hrs 20mins +/- 8mins
Average Peak Load (kW)	the customer's average peak demand, based on the highest load aggregated from three consecutive 20min intervals during each 27hrs 20mins period
Electricity Rate	the contractual electricity tariff, mainly 3 categorical attributes: Normal rate, Economic rate, and Time rate
Housing Type[2]	historical statistics, including 4 categorical attributes: Summer Cottage, Detached House, Town House, Multi-storeyed Building
Seasonal and day-of-the-week Consumption (kWh)	includes Weekday, Weekend, Jan.-Apr., May-Sep., Oct.-Dec., Winter (Oct.-Feb.), and Summer (March-Sep.) consumptions
Time-based Peak Load (kW)	the customer's average peak demand at various times of the day, including: Peak Load_Day, Peak Load_Night; Peak Load_6-9, Peak Load_9-16, Peak Load_16-22, and Peak Load_22-6

Table1. Summary of Variables

[1] Some people argue that data for real-time BI only needs to be as fresh as the decision or business process require. Depending on the business need, data can be hourly, daily, and even weekly or monthly and still be real-time (Anderson-Lehman et al., 2004).

[2] Categorical variables, such as Electricity Rate and Housing Type, must be split into binary dummy variables in order to be used with the SOM, as they represent nominal data with no inherent numerical order or distance.

In this study, Viscovery SOMine v.5.0 is used to perform the visual data mining task. SOMine uses an expanding map size and the batch training algorithm, allowing for efficient training of maps (Deboeck and Kohonen, 1998). The SOM-Ward clustering method is also used to identify clusters based on actual consumption behaviour, which eliminates the need for subjective identification of clusters (Vesanto and Alhomiemi, 2000). The seasonal and time-based variables are normalised according to their respective average values before map training, i.e., each entry in a field is divided by the mean of the entire field (Collica, 2007). The purpose is to address the relative significance of the value of a particular variable against the overall mean of that variable. In addition, all the variables included in the training process were scaled to comparable ranges in order to prevent variables with large values from dominating the result. Viscovery SOMine offers two forms of scaling, linear and variance scaling. Linear scaling is based upon the range of the variable, and is suggested as default when the range of the variable is greater than eight times of its standard deviation. Otherwise, variance scaling is used. In this study, range scaling was applied to the variables of Electricity Rate and Housing Type, while variance scaling was applied to the others.

We experimented with different combinations of parameters, and selected the map based on following criteria: average quantization error, normalized distortion measure, the meaningfulness of clusters, the visual interpretability, the smoothness of neighbourhood of each node, and the SOM-Ward cluster indicator. The map was trained using a map size of 279 nodes, a map ratio of 100:49, and a tension of 0.5. During the training process, the priority of categorical variables such as Electricity Rate and Housing Type, as well as the seasonal and time-based variables proposed by the authors, was set to 0.

In order to evaluate the robustness of the training method, a supervised ten-fold cross-validation was conducted. The entire training dataset was firstly partitioned into 10 subsets, then using 9 out of the 10 subsets each time to reiterate the map training with the same set of training parameters as was described above. The map selecting criteria set above can be held over the ten-fold iteration.

5. RESULTS AND ANALYSIS

5.1. Cluster Profiles

The 11,964 customers are grouped into 4 clusters according to their consumption similarity in 2009. The results can be seen in Figures 3-5. Since the warm colour code (e.g., red) in SOM maps denotes high values while a cold colour code (e.g., blue) represents low values, the characteristics of each cluster (I-IV) can be easily identified, as summarized in Table 2.

ID	Consumption Rank	Daily Consumption (kWh)	Average Peak Demand (kW)	Cluster Size and Percentage of Total Consumption (%)	Cluster Profile
I	High consumption	63.0	5.1	10.0, 28.9	Highest electricity demand, Highest proportion (19%) for Economic rate, The majority (88%) lives in detached house, while 7% in summer cottage, 4% in town house, and 1% in multi-storeyed building.
II	Medium-high consumption	39.3	3.2	17.0, 30.7	Medium to high electricity demand, The majority (94%) for Normal rate, while 5% for Economic rate, The proportion of summer cottage (18%) is the second highest after cluster IV, while the majority (75%) is in detached house, 6% in town house, and 1% in multi-storeyed building.
III	Medium-low consumption	20.3	2.0	25.9, 24.1	Medium to low electricity demand, Similar characteristics as those of cluster II, e.g., 96% for Normal rate and 75% in detached house, The proportion of town house is the highest (12%), while 9% in summer cottage and 4% in multi-storeyed building.
IV	Low consumption	7.5	0.6	47.1, 16.2	Lowest electricity demand, 99% for Normal rate, Highest proportion (70%) of summer cottage, while 18% is detached house, 8% town house, and 4% multi-storeyed building.

Table2. Summary of Cluster Characteristics

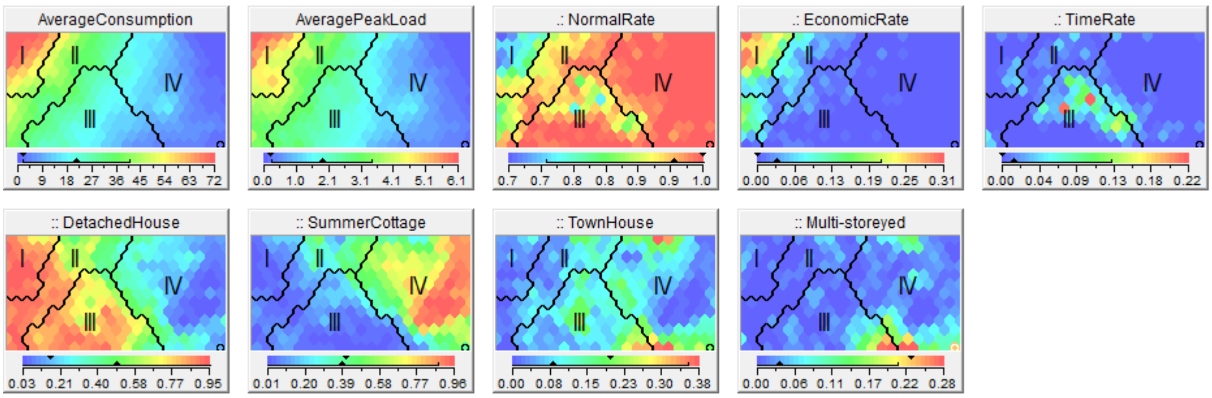

Figure3. Cluster Profiles

5.2. Consumption Time Series Profiling

The consumption pattern profiling is carried out with a focus on two types of consumption time series, including (i) consumption seasonality, and (ii) load patterns at various times of the day (i.e., different time bands).

5.2.1. Consumption seasonality

The customers' seasonal consumption patterns vary. They follow the typical Nordic phenomena: electricity consumption is relatively higher in cold winter months than in summer time. This can be seen from both sets of seasonal consumption variables (see Figure 4 a. & b.). However, it is important to note that there is a special group of customers in cluster IV (see Figure 5), whose electricity consumption in May-September is higher than the rest of cluster IV. This special group can be identified both from Figure 5a. (May-Sep. Consumption) and Figure 5b. (SummerConsumption), which emphasizes that the consumption deviation of this special group of customers in summer time is without regard to the summer months partition (i.e., May-September vs. March-September). At this point, it demonstrates that such a SOM-based data mining approach can visualize latent information for companies to take action upon.

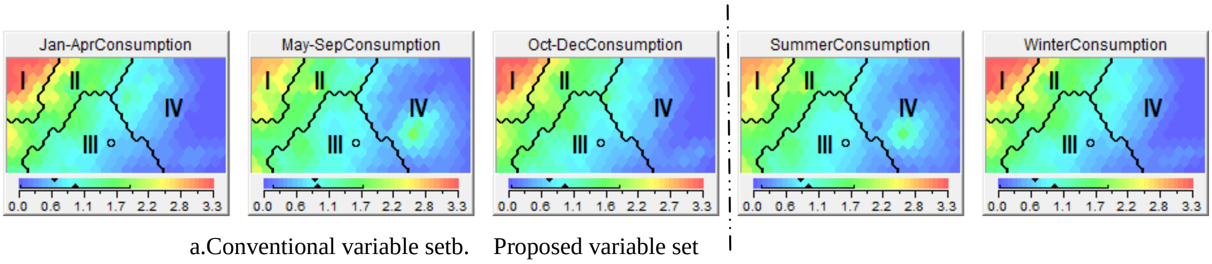

Figure4. Seasonal Consumption Visualization

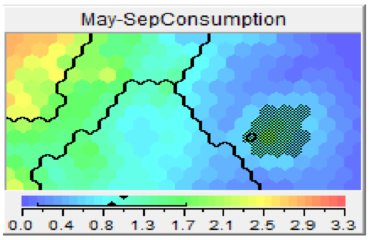

Figure5. Special Customer Group Visualization

Based on the SOM visualization results, Figures 6 and 7 summarize the comparison of various time series profiles among clusters. Figure 6 illustrates the consumption profile breakdown of each cluster and the special group within cluster IV, regarding weekday/weekend as well as seasonal consumption patterns. The different clusters have distinct consumption profiles in different seasons. For instance, regarding the Medium-low consumption customers (cluster III), their electricity usage is relatively even across different seasons (Jan-Apr., May-Sep. and Oct.-Dec.) in 2009 (red line in Figure 6). But High and Medium-high consumption customers (purple and green lines in Figure 6) had lower electricity consumption in summer time, compared to their respective cold weather seasons. On the other hand, as was pointed out before, among Low consumption customers, their consumption between May-September is relatively higher than in the rest of the seasons (see two blue lines in Figure 6). Additionally, it needs to be noted that there is no significant variation between weekday and weekend consumptions within each cluster. This implies that in order to shift customers' demand between weekday and weekend to mitigate system constraints or when the wholesale market price is high, the utility should devise enough incentive in their price signals for customers to adjust their consumption behaviour between weekday and weekend.

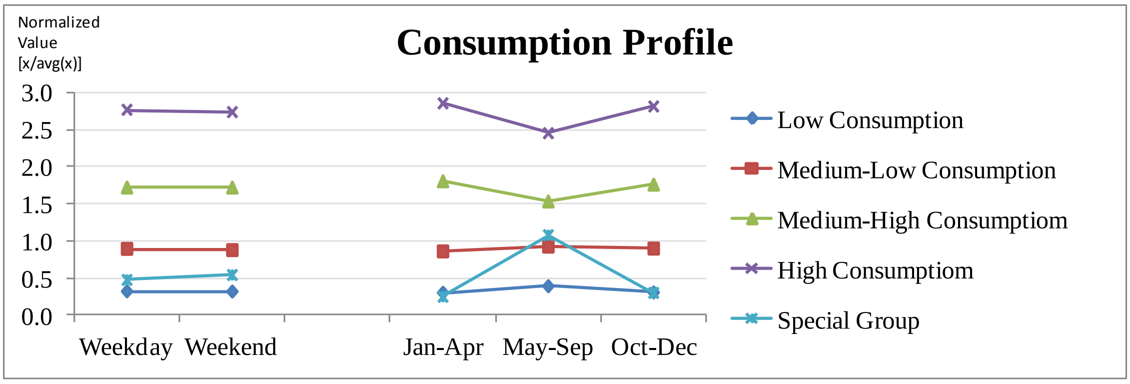

Figure6. Consumption Profile Breakdown

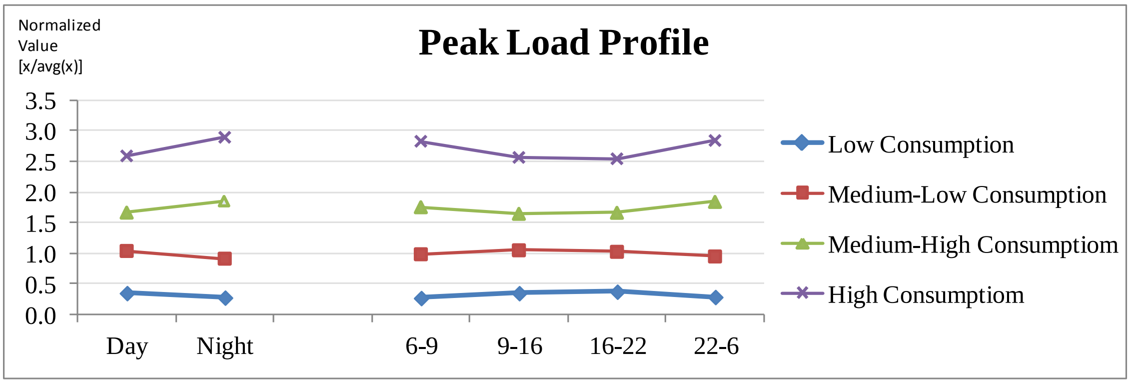

Figure7. Peak Load Profile Breakdown

5.2.2. Load patterns at various times of the day

Figure 7 shows a different picture regarding Peak Load at Day- and Night- time on the left hand side compared to that in 4 time bands on the right hand side. For instance, the peak load of High consumption customers (purple line on the left) is slightly higher at night (23:00-7:00) than during day time (7:00-23:00). However, if one looks at the 4 time bands on the right, the High consumption customers have relatively higher peak demand in the early morning (6:00-9:00) and during the night (22:00-6:00), compared to usual working hours (9:00-16:00) or usual peak consumption time period (16:00-22:00), where the purple line bends up towards the ends considerably. This suggests that using the 4 time bands can reveal more detailed information about the customers' consumption behaviour. It might be beneficial if the utility would consider using more than 2 time bands in their Time-of-Use pricing.

6. IMPLICATIONS

The results indicate that a few actionable insights about the customer's electricity consumption patterns have been extracted by such an analytical approach. These findings could guide the company's management team to formulate new pricing differentiation strategies. For instance, would it be beneficial to offer special electricity tariff to the customers who have higher summer consumption need? Or, to which extent does the price signal provide adequate incentive to steer the weekday and weekend consumption shift in light of the wholesale market price?

Nonetheless, this application only demonstrates one feasible step on the way to build a real-time BI-enabled business model. In order to answer the questions raised above, a holistic BI approach is required. As illustrated in Figure 9, apart from AMR and customer demographics system, the operational systems which contain other internal data such as financial data, service data, and billing system data, as well as external data sources such as regulatory data, weather, wholesale market price, etc., also need to be integrated through data warehousing, in order to support designing new product/price mix, or innovative business.

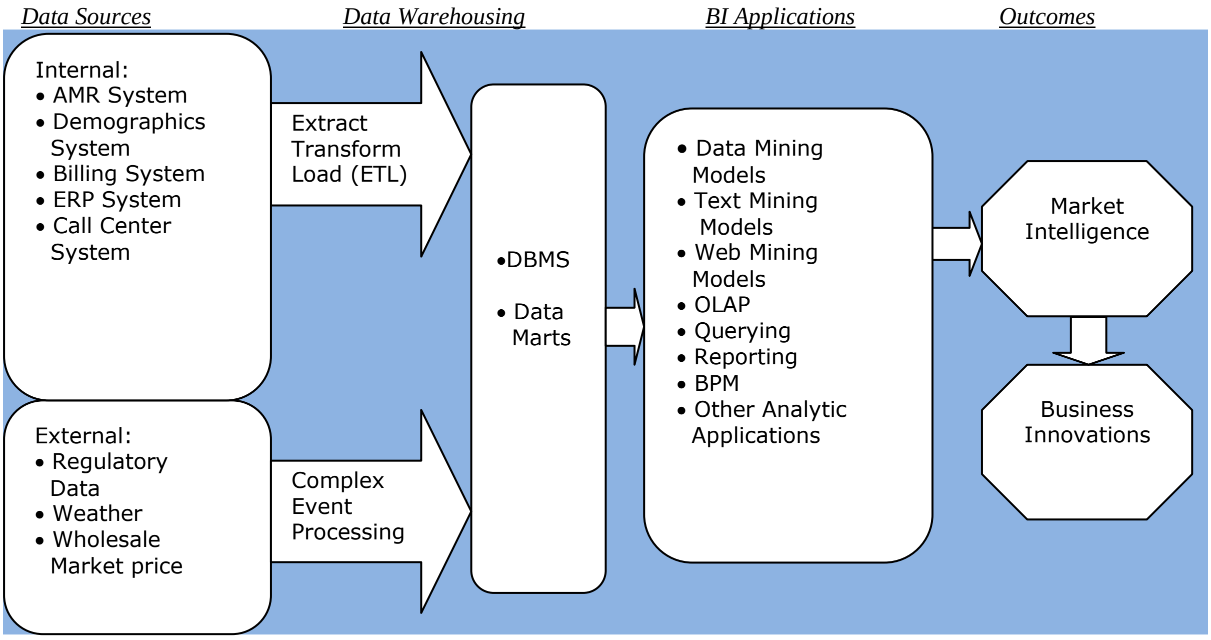

Figure9. Real-Time BI Framework for Demand Response

Imaging if the real-time BI architecture is in place, and provided with hourly or half-hourly measured AMR data, it will allow the company to update their understanding of the customer's consumption profile in a near real time manner. With the gained better knowledge of customers' electricity demand, the company's decision makers can differentiate their pricing strategy when such a business need arose. For example, in the demand response scenario, the company can suggest a lower tariff at certain point of the day to a particular customer group, in order to serve the purpose of mitigating electricity demand from a critical peak period to off-peak time. The selection of the particular customer group is based on the up-to-date and accumulated knowledge of the customer's consumption profile and the willingness and feasibility of the customer to respond to the price signal. This capability of steering electricity demand is crucial for the electricity utilities to outperform under the complex demand-supply dynamics of electricity supply. It is also significantly important with respect to integrating the intermittent renewable energy resources into the electricity supply scene, which is another business challenge faced by the electricity industry. Therefore, we believe that the real-time BI enterprise architecture as proposed in this paper will enhance the company's management capability to achieve the goal of 'from intelligence to innovation'.

7. CONCLUSION

Real-time BI is widely recognized as a critical enabler of value creation and business innovation both in IS literature and in practice. Taking a holistic view of BI, this study demonstrates a data mining driven approach in the effort of turning smart meter data into market intelligence for innovative business development. The empirical findings imply that overall real-time BI enterprise architecture is the key for innovative initiatives. And the BI-based management capability will lead an organization to sustainable profitable growth.

This study is part of an ongoing research project. Future work will involve field testing both for the evaluation of the data mining model and for the validation of the overall BI framework. Moreover, the feasibility and generalizability of this construct needs to be investigated with hourly measured smart meter data.

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ISBN 978-952-12-2715-8