SMART METERING AND CUSTOMER CONSUMPTION BEHAVIOUR PROFILING -- EXPLORING POTENTIAL BUSINESS OPPORTUNITIES FOR DSOS AND ELECTRICITY RETAILERS

Hongyan LIU
Turku Centre for Computer Science (TUCS) / Åbo Akademi University – Finland
hliu@abo.fi

Tomas EKLUND
Turku Centre for Computer Science (TUCS) / Åbo Akademi University – Finland
toeklund@abo.fi

Barbro BACK
Turku Centre for Computer Science (TUCS) / Åbo Akademi University – Finland
bback@abo.fi

ABSTRACT

With the implementation of smart metering in Finland by 2013, the distribution system operators (DSOs) and the electricity retailers need to explore new business opportunities enabled by this development. In this study, we investigate a business intelligence approach – customer electricity consumption behaviour profiling, in the attempt of comparing customers' electricity rate choice according to their actual consumption. We cluster customers in the Åland area of Finland with Self-Organizing Maps, based on measured electricity consumption data for 2007-2009. The results suggest that customer consumption behavior profiling could allow the DSOs and electricity retailers to better understand their customers. Such a business intelligence approach highlights the business potential to extend targeted marketing or dynamic pricing for the electricity distribution and / or retail companies.

INTRODUCTION

With the large scale smart meter roll-out in Finland, all Finnish commercial customers and residential consumers will have remotely-read electricity meters by the end of 2013. The distribution system operators (DSOs) and the electricity retailers are imminently facing issues including: 1) how to fully utilize this investment and technological advance to enhance their day-to-day operations, 2) how to continuously improve cost efficiency, and 3) how to create new growth opportunities sustainably. Here, we propose a business intelligence approach, namely customer consumption behavior profiling, which we believe is the next step in the effort to develop dynamic price-based demand response applications, new energy and price mixes, and a more active electricity retail market.

The prevailing pricing models [1], [2] are mainly based on customer categories (i.e., industry, service and trade, housing, etc.), or housing type in the case of residential consumers. It is highly likely that even in the same customer category / housing type, the consumption patterns may vary considerably due to customers' business nature / life style diversity [3]. Before the implementation of smart metering, it was impossible to accurately identify real-time customer consumption patterns on a large scale.

The aim of this study is to apply a data mining technique in the form of the Self-Organizing Map (SOM) to group customers according to their actual consumption. We investigate 14,000 Finnish customers' longitudinally measured electricity consumption data during 2007-2009. The data are provided by one regional DSO – Ålands Elandelslag (ÅEA, a non-profit ownership cooperative), whose distribution area has distinct geographical features and customer structure. We profile the customers without regard to their conventional classification (i.e., customer categories and housing type). Then, we compare their contractual electricity rates in light of their actual consumption patterns.

The questions of interest are the following: (i) Can the SOM-based approach provide added value to the DSOs and electricity retailers? (ii) How can a business intelligence approach built upon smart metering contribute to obtaining and maintaining an efficient and well-functioning electricity retail market in the long run?

In the next section, we will briefly introduce the Åland area and the SOM method. Thereafter, the experiment and the results will be presented. Conclusions will be drawn in the final part of this paper, together with proposals for further research.

BACKGROUND

The Åland area

Åland is a Finnish archipelago region with nearly 300 habitable islands, which is situated in between mainland Finland in the east and Sweden in the west. It consists of 16 municipalities with Mariehamn as the regional capital. ÅEA is responsible for the electricity distribution to 15 municipalities (excluding Mariehamn). Its distribution area covers 14,097 customers, of which Jomala is the largest (2,290) and Sottunga is the smallest (184 customers).

Åland's geographical features determine that its economy is heavily dominated by shipping, trade, and tourism. The majority of the housing is in the form of summer cottages, detached houses, or town houses, while multi-storeyed buildings only account for a very small portion.

According to Statistics Åland, in 2009, Åland's electricity consumption by sector is as follows: Households (45.04%), Agriculture (7.01%), Industry (11.77%), Services (21.22%), and the Public Sector (14.97%), respectively. It shows that households, services, and the public sector constitute the majority in terms of electricity consumption in Åland. This differs from the electricity consumption breakdown on mainland Finland, where industry's electricity consumption amounts to 46%, whereas housing and agriculture, and services and construction, consume 29% and 22% respectively (source:Energiateollisuus).

The SOM method

The Self-Organizing Map (SOM) is a data-mining approach based upon Artificial Neural Networks (ANNs). ANNs are designed to mimic the basic learning and association patterns of the human nervous system, and consist of a number of neurons (simple processors) connected by weighted connection. ANNs learn by adjusting the weight of each connection, increasing or decreasing the importance of the input (information) being transferred, until a desired output is achieved. Essentially, they are non-linear, multivariate regression techniques, better able to handle erroneous and noisy data than parametric statistical tools [9].

The SOM is a two-layer ANN that uses the *unsupervised* learning approach, i.e., SOM does not require target output values for training [11]. The essence of the SOM is to map high dimensional data onto a spatial map (usually in the form of a two-dimensional lattice of hexagonal nodes). The SOM uses the *competitive learning* algorithm, meaning that the nodes on the output layer compete with each other to be the best matching node (i.e., the winner) whose connection weights to the input pattern are the closest in terms of the *Euclidian distance*. At the same time, the SOM algorithm allows the output nodes in the neighborhood of the winner to adjust their weights accordingly. Theoretically, all the nodes on the output layer are the projection of the input data items. As such, the intrinsic relationships (e.g., similarities) of input data in the multivariate space are reflected on a two dimensional *topological map*, i.e., visual clustering is performed [10], [11]. In addition, the variables which are used for training the map are usually displayed in color as *feature planes*, with 'warm' colors representing high values while 'cold' colors for low values (see Fig. 2). Therefore, it is easy to visually interpret the characteristics of each cluster from the feature maps.

In addition to many applications in finance, medicine and engineering [4], the Self-Oranizing Map (SOM) has been used in the energy sector for e.g., power system stability assessment, on-line provision control, and load forecasting [5], [6], [7], [8]. Like other artificial neural networks (ANNs), the SOM is acknowledged for its robustness in handling non-linear and multivariate data, especially with regards to dimension reduction and large datasets. In particular, the SOM is recognized for its visualization capabilities. Compared to other clustering techniques, the SOM does not require predefining a desirable number of clusters, which means that little *a priori* knowledge of the data is required. For these reasons, this study seeks to apply the SOM in the field of electricity customer consumption behavior profiling in the Åland context. To our knowledge, the SOM has not been previously applied in this domain.

In this study, Viscovery SOMine v.5.0 (http://www.eudaptics.com/) is used. SOMine uses an expanding map size and the batch training algorithm, allowing for very efficient training of maps [11]. SOM-Ward clustering method is also used to identify clusters based on actual consumption behavior, which eliminates the need for subjective identification of clusters [12].

THE EXPERIMENT AND RESULTS

The experiment

The data used in this study are from ÅEA meter readings for the period of 2007-2009. For each meter, the readings are registered with 27 hours 20 minutes time intervals, due to the communication technology adopted (Turtle Automated Meter Reading system.) The variables included in the analysis are as follows:

Consumption (kWh) – is derived from consecutive readings which are measured per 27hrs 20mins +/- 8mins.

Peak Load Value (kW) – is the highest load aggregated from three consecutive 20min intervals during each 27hrs 20mins period.

Tariff Code (TaCo) – is the contractual electricity rate the customer has chosen from 5 categories: Normal rate, Economic rate, Time rate, Irrigation rate, and Temporary Working rate, which are provided by ÅEA (available at http://www.el.ax/files/tariffhafte_20110101.pdf, in Swedish).

Housing Type (HoTy) – is based on historical statistics, provided by ÅEA as a reference variable, including 5 categorical attributes: Summer Cottage, Detached House, Townhouse, Multi-storeyed Building, and Others.

Results

We will present two municipalities' (Brändö and Geta) results in the following. The reason for selecting these two municipalities is because they have a similar customer base size (Brändö: 600, Geta: 667), but their geographical features and customer composition differ significantly. For instance, Brändö is in the northeast of Åland's territory, where out of 1,648.51 square kilometers, 1,540.44 km^2 is water (93%). Geta, on the other hand, is connected to the mainland of Åland, and its size is 606.56 km^2, of which about 86% is water. Table 1 illustrates the differences in customer composition between Brändö and Geta.

Table 1 Number of enterprises in Brändö and Geta in 2007 (source: Statistics Åland)

	Brändö	Geta
Agriculture, forestry, and fishing	10	1
Industry	7	3
Construction	13	12
Trade, hotel	19	10
Transport	10	2
Finance and insurance	6	5
Public services	7	0
Total	72	33

Fig. 1 & 3 present the clustering results, where Brändö results in 6 consumption groups (B1-B6) while Geta has 5 clusters (G1-G5). The feature planes (Fig. 2 & 4[1]) and cluster characteristics breakdown (Table 2 & 3) reveal some interesting facts: In Brändö, cluster B1 has the highest average values in terms of Consumption and Peak Load (235 kWh, 19.88 kW), and 29.8% customers in B1 chose Time rate while 70.1% of them adopted Normal rate. On the other hand, cluster B2 has the second highest value in Consumption and Peak Load (94 kWh, 7.67 kW), and the customers' choice of contractual electricity rate differs – 34.5% chose Economic rate, 64.4% went for Normal rate, and 1.1% had Time rate. The majority of the customers (65.66%) are in cluster B5, which has the lowest average Consumption and Peak Load values (7 kWh, 0.47 kW). There are 3.3% and 1.3% customers who adopted Economic rate and Time rate respectively in B5. Customers in B3, 4, & 6 identically preferred the Normal rate, but their consumption profiles can be identified based upon their housing types. In Geta, similar features as for B3, 4, & 6 in Brändö can also be seen in G3, 4, & 5. Even though the majority of the customers in Geta have chosen the Normal rate (e.g., G 3, 4, & 5), the customers in G1 & 2 differ from the others. The average Consumption and Peak Load values in G1 are the highest among the 5 clusters (205 kWh, 15.22 kW). 61.9% of the customers in G1 chose the Economic rate, while the remaining 38.1% still chose the Normal rate. No customers use the Time rate. On the other hand, in G2 the customers' average Consumption is ranked the second highest (68kWh), and the average Peak Load Value (5.46 kW) is slightly lower than the second highest value in G5 (5.81 kW). However, 8.3% and 3.8% of the customers in G2 have chosen the Economic- and Time- rate, respectively.

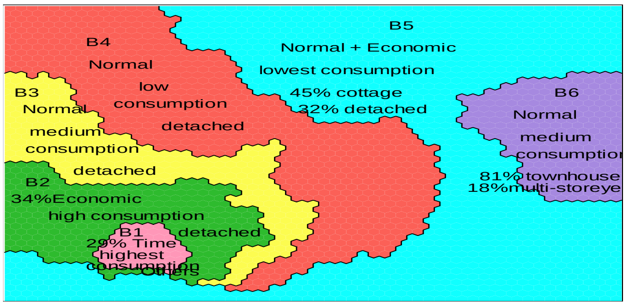

Fig. 1 Brändö consumption clusters

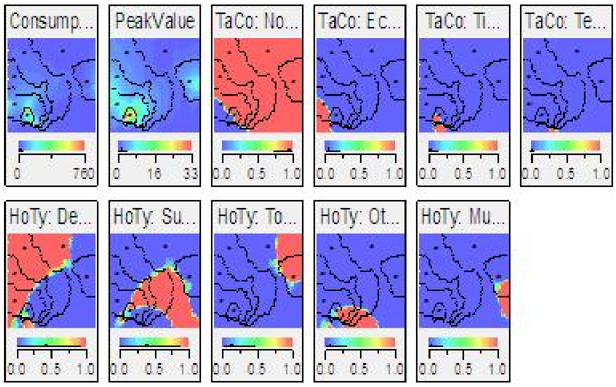

Fig. 2 Feature maps of Brändö clusters

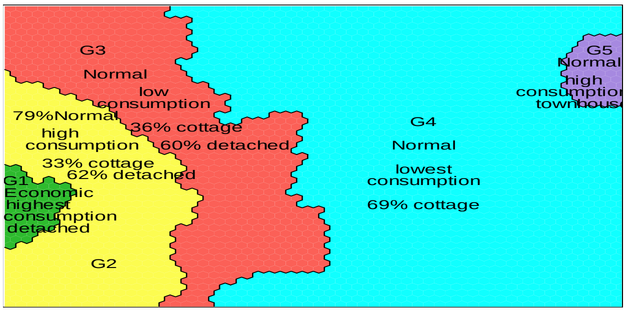

Fig. 3 Geta consumption clusters

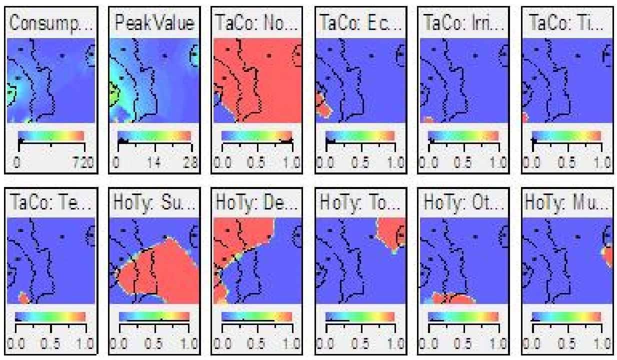

Fig. 4 Feature maps of Geta clusters

1 The figures can only be interpreted in color format.

Table 2 Characteristics of clusters in Brändö

	B1	B2	B3	B4	B5	B6
Cluster size %	0.42	4.33	6.37	18.84	65.66	4.38
Consumption kWh	235	94	47	27	7	42
Peak Load kW	19.88	7.67	4.66	2.22	0.47	4.22
Normal Rate %	70.1	64.4	100	100	95.1	100
Economic Rate %	0.1	34.5	0	0	3.3	0
Time Rate %	29.8	1.1	0	0	1.3	0
Temp. Rate %	0	0	0	0	0.3	0
Detached %	1.8	64.9	75.7	66.4	32.1	0
Sumer Cottage %	30.1	22.4	19.9	30.0	45.6	0
Townhouse %	0.2	0	0	0	13.0	81.7
Others %	67.8	12.6	4.4	3.6	6.8	0
Multi-storeyed %	0	0	0	0	2.6	18.3

Table 3 Characteristics of clusters in Geta

	G1	G2	G3	G4	G5
Cluster size %	1.04	8.41	15.42	73.95	1.18
Consumption kWh	205	68	34	7	66
Peak Load kW	15.22	5.46	2.95	0.58	5.81
Normal Rate %	38.1	79.5	100	100	100
Economic Rate %	61.9	8.3	0	0	0
Irrigation Rate %	0	5.4	0	0	0
Time Rate %	0	3.8	0	0	0
Temporary Rate %	0	3.1	0	0	0
Summer Cottage %	12.0	33.3	36.9	69.6	0
Detached %	87.9	62.4	60.7	18.7	0
Townhouse %	0.1	0	0	7.6	96.5
Others %	0	4.3	2.4	3.0	0
Multi-storeyed %	0	0	0	1.1	3.5

CONCLUSION

In this study we use the SOM to profile customers in the Åland area, based on their measured electricity consumption data. Our purpose is to examine what kind of benefits a business intelligence approach can offer to DSOs or electricity retailers. The results indicate that the majority of customers in cluster B1(70.1%), B2 (64.4%), and G2 (79.5%) – which have high consumption profiles in their respective municipalities – chose the Normal rate, instead of the Economic- or Time- rates, which should favor customers with high consumption. The reason behind might lie in the fixed components of the tariffs, but illustrates well how consumption profiling could be beneficial. To this end, we perceive that a SOM-based customer consumption behavior profiling method can provide added value to DSOs or retailers, though it requires further examination to evaluate the profiling results. Additionally, it implies that if analyzing customers according to their consumption similarity and / or deviation, it will assist DSOs and retailers to develop a better understanding of their customers, which in turn could aid them to design electricity rates that can facilitate demand response applications. For example, the attributes of customers in G1 (with high consumption profile) and especially B5 (with low consumption profile), who favor of Economic- or Time- rate, could be good indicators to gauge other customers who share similar attributes for Time-of-use (TOU) rate promotion. Meanwhile, through encouraging more customers to adopt TOU rate, DSOs can better mitigate the peak load formation in line with the supply capability, in order to secure the quality of supply. Hence, we can argue that a data-mining based business intelligence approach is a promising starting point in the effort to obtain and maintain an efficient and well-functioning electricity retail market in the long run.

Acknowledgements

The authors would like to thank Ålands Elandelslag (ÅEA) for providing the data for this study. The authors also gratefully acknowledge the financial support of the Academy of Finland (grants no. 127656 and 127592).

REFERENCES

[1] M. Räsänen, J. Ruusunen, and R. P. Hämäläinen, 1995, "Customer level analysis of dynamic pricing experiments using consumption-pattern models", Energy, vol. 20, no. 9, 897-906.

[2] M. Räsänen, J. Ruusunen, and R. P. Hämäläinen, 1997, "Optimal tariff design under consumer self-selection", Energy Economics, vol. 19, 151-167.

[3] J. Keppo and M. Räsänen, 1999, "Pricing of electricity tariffs in competitive markets", Energy Economics, vol. 21, 213-223.

[4] M. Oja, S. Kaski, and T. Kohonen, 2002, "Bibliography of Self-Organizing Map (SOM) Papers: 1998-2001 Addendum", *Neural Computing Surveys*, vol. 3, 1-156.

[5] A. Lendasse, J. Lee, V. Wertz, and M. Verleysen, 2002, "Forecasting electricity consumption using nonliner projection and self-organizing maps", *Neurocomputing* vol. 48, 299-311.

[6] T. N. Nababhushana, K. T. Veeramanju, and Shivanna, 1998, "Coherency identification using growing self organizing feature maps (power system stability)", *IEEE Proceedings of EMPD '98. International Conference on Energy Management and Power Delivery*, vol. 1, 113–116.

[7] C. Rehtanz, 1999, "Visualisation of voltage stability in large electric power systems", *IEEE Proceedings Generation, Transmission and Distribution*, Vol.146, 573–576.

[8] J. Riqueline, J. L. Martinez, A. Gomez, and D. C. Goma, 2000, "Possibilities of artificial neural networks in short-term load forecasting", *Proceedings of the IASTED International Conference Power and Energy Systems*. IASTED/ACTA Press, Anaheim, CA, USA, 165–170.

[9] C. M. Bishop, 1995, *Neural Networks for Pattern Recognition*. Oxford University Press, Avon.

[10] S. Haykin, 1999, *Neural networks: a comprehensive foundation, 2nd ed.*, Prentice Hall, Upper Saddle River, New Jersey.

[11] T. Kohonen, 2001, *Self-organizing maps, 3rd ed.*, Springer, Berlin, Germany.

[12] J. Vesanto and E. Alhoniemi, 2000, "Clustering of the self-organizing map", *IEEE Transactions on Neural Networks*, vol. 11, issue 3, 586-600.