International Conference on Applied Energy
ICAE 2012, Jul 5-8, 2012, Suzhou, China
Paper ID: ICAE2012- A10599

ENERGY DEMAND MODEL DESIGN FOR FORECASTING ELECTRICITY CONSUMPTION AND SIMULATING DEMAND RESPONSE SCENARIOS IN SWEDEN

Javier Campillo[1,2], Fredrik Wallin[1], Daniel Torstensson[1], Iana Vassileva[1]

[1]School of Sustainable Development of Society and Technology, Mälardalen University, SE-721 23 Västerås, Sweden
[2]Facultad de Ingeniería, Universidad Tecnológica de Bolívar, CO-160002 Cartagena, Colombia

javier.campillo@mdh.se
+46 0 21 10 7076

ABSTRACT

The introduction of a deregulated power system market and development of smart-metering technologies in Sweden, bring new opportunities for fully exploiting its power system efficiency and reliability, such as price-based demand response (DR) programs at a large scale for household, commercial and industrial users.

The deployments of these DR programs require, however, very accurate demand forecasting models. The traditional approach of obtaining the total energy use and peak demand does not offer the required detailed information. This article reviews several methodologies for forecasting electricity consumption from a bottom-up perspective in order to define the required parameters and structure for obtaining an energy model. This model will finally include energy usage data, behavioural parameters obtained from a survey conducted with 5 000 end-users in different Swedish distribution system operators' areas, and physical conditions for the facilities (internal/external temperatures and insulation materials). This information is provided from previous research studies performed at Mälardalen University and Swedish electric utilities companies.

The obtained model should be able to adjust its parameters dynamically in order to simulate several demand-response scenarios based on four different strategies: time of use pricing, use of curtailable/interruptible rates, imposition of penalties for usage beyond predetermined levels, and real time pricing.

Keywords: smart-grids, demand-response, electricity forecasting, load consumption, electricity market

1. INTRODUCTION

The Nordic electricity production system consists of a mixture of several sources such as wind, hydro, nuclear and biomass powered thermal power. Hydropower is the major source of electricity generation in the Nordic region; It accounts for more than half of the total production capacity.[1]

In 2010, total electricity production in the Nordic countries was 373.3 TWh, an increase of 1% compared to 2009. The same year, electricity demand was 396 TWh, an increase of 3.8% compared to 2009. The largest rise in consumption was in Finland, due to the recovery of energy intensive industries after the financial crisis. There was also an increase in the load due to significant low temperatures in the region during that winter season.[2]

Abundant precipitation, mountainous ridges and windy spots have allowed the Nordic countries to produce cheap electricity, resulting in the highest demand for electricity per capita all over Europe [3]. This high demand and the high dependence on water inflow and reservoirs level, makes the system very sensitive to environmental factors. 2010 was a very dry year and the temperatures during winter season were lower than usual, resulting in production deficit of 30TWh, and a price increase in the electricity spot price compared to 2009. In Sweden alone, In February 22nd, 2010, at 8 am, the electricity spot price was 1400 EUR/MWh, about 25 times higher than the average price.

During the rest of the year, the mean spot price in Sweden was 54.48 EUR/MWH, the highest annual mean price even recorded. [4]

According to a model analysis included in [4], increased demand flexibility are the easiest way to influence pricing situations where production capacity approaches levels when peak load reserves are needed, resulting in electricity high price spikes.

In a more detailed study about Sweden´s demand flexibility presented in [5], there is great potential for demand flexibility in the industrial sector, specially within the paper industry.

For households, there is a great potential for encouraging the adoption of demand-response programs by implementing different pricing mechanisms, such as time-of-use billing, demand-based pricing, hourly etc., several authors have analysed the impact of these mechanisms in

[6–8], and the new opportunities for the Swedish electricity market.

The introduction of the new legislation and adoption of remote meters in 2009, in combination with more flexible pricing schemes, offer a great opportunity for Sweden to maintain more stable prices during high-demand conditions such as the one in Feb 22, 2010 by adopting more flexible demand-response strategies.

This will also play an important role when renewable generation is introduced on a large scale in the forthcoming years. Sweden's national planning target for electricity production from wind power is 30 TWh by 2020, of which 10 TWh are to be offshore; further, in July 2009, Parliament set a new goal of 25 TWh generation from renewable energy sources by 2020 [9]; demand response will be required in order to add stability to the system.

In order to design appropriate demand response programs, accurate energy demand-consumption models should be developed to simulate different scenarios for industrial, commercial and household users. Traditional models forecast demand consumption based on the previous consumption data in a top-down approach; a bottom-up approach should be addressed to overcome the limitations of the former, such as the inability to predict consumption patterns changes like the implementation of flexible demand consumption, distributed generation and adoption of new technologies.

2. MODELING APROACHES

In a deregulated market, such as the Nordic one, demand forecasting is vital for the electric industry. Forecasting models are used to set electricity generation and purchasing, establishing electricity prices, load switching, demand response and infrastructure development.

Several methods for developing these models have been developed over the years; these methodologies can be classified in short-term and long-term forecasting [10], Also, depending on the approach, the forecasting can be made from an aggregated level (e.g. from the electric utility side) in a top-down scheme, or from the user side, analysing end-use activities, in a bottom-up scheme.

The method to apply is chosen based on the nature of the available data and the desired nature and detail level of the forecasts.

2.1 Short-term Forecasting

Short-term forecasting is usually done from one hour to one week [10], and it plays a very important role in the operation of power systems' basic operating functions such as energy transactions, unit commitment, security analysis, economic dispatch, fuel scheduling and unit maintenance. [11]

2.1.1 Trend Method

This method expresses the variable to be predicted as a function of time. It is a non-causal method, therefore, it doesn't explain the behaviour of the trend line; it exclusively makes a projection based on the historical data.

The main advantage of using this method is its simplicity and that only historic consumption data is required. Also, it is possible to achieve high of accuracy for short-term forecasting [10], [11]. Commercial software tools for companies and energy traders frequently use this approach. [12],[13], [14]

Some of the techniques used for this type of forecasting are multiple regression, exponential smoothing, iterative weighted least squares and stochastic time series. Its comparison are performed in [15].

The main limitation of the Trend Method is that, since it does not include any type of demographic, socio-economic or end-use data as, it cannot predict changes in the consumption behaviour, adoption of new technologies or changes in policies for electricity use, required for infrastructure planning, policy changes and technology adoption.

2.1.2 Similar Day Approach

This method analyses the natural pattern of the power load and the forecasting day´s weather features to define specific parameters that can be compared to previous days with similar characteristics. This information is used to create a training data bank to feed pattern recognition tools, in order to emulate the non-linear relationships between load demand and the factors that influence it. The most common pattern recognition tools used are artificial neural networks (ANN)[16–18], expert systems, fuzzy logic [19] and support vector machines (SVM)[20][21].

ANN is still the most used method for this approach, due to its ability to learn complex and non-linear relationships [18], the availability of commercial tools for its implementation, the operational speed for pattern recognition once the network has been trained, and the high level of accuracy that can be obtained from this approach. A.J. Al-Shareef, et al achieved an accuracy of 1.12% for one-hour ahead forecasting using an ANN-based short-term model [17]. Paras Mandal et al, achieved an accuracy of 0.8% for one hour ahead forecasting and 2.43% for six hours ahead forecasting. [18]

Some limitations for the use of ANN for similar-day approach are the accuracy required for the training data set and the impact of the ANN architecture design and the training algorithm selection.

In order to overcome ANNs limitations, the use of Support-Vector-Machines (SVM) have been used lately for improved short-term forecasting. SVM's use a similar approach to that used by ANNs, but offers a higher calculated accuracy and shorter training times [21], [20].

Both, the trend method and the similar day approach, use a top-down approach because short-term forecasting is mainly used by utilities and the users energy consumption aggregated information is easily available for them.

2.2 Long Term Forecasting

Long-term forecasting plays a very important role in policy formulation and supply capacity expansion. Since the impact of the adoption of new technologies and policies affects the demand itself, combined methods are usually employed in order to include as many relevant factors as possible. These factors include consumer behaviour, technology adoption impact and simulated scenarios.

2.2.1 End-Use Method

This method analyses the impact of energy usage patterns of different devices/systems in the overall energy consumption in a disaggregated approach. For residential users, appliances, house´s sizes, equipment´s age, customer behaviour and population dynamics are often included [22], [10], [23].

End-use models are based on the principle that electricity demand is derived from users' demand for individual requirements (e.g. lighting, cooling, etc.), therefore, these models are suitable for predicting demand changes with the adoption of new technologies, use of new policies or implementation of demand response programs. This demand prediction capability is necessary for long-term forecasting and helpful for the adoption of energy-efficiency programs.

To build an energy model using an end-use method, less historical data is usually required, compared to the trend method or the similar day approach; however, it requires a lot more detailed information about the consumers the model is based upon. [10]

Even though the end-use method is mainly a bottom-up approach, several authors have developed algorithms to obtain the end-use load profiling in an unobtrusive way (e.g. Non-Intrusive Load Monitoring), using the aggregated energy consumption data from the main meter in a top-down scheme [24–30]. The accuracy obtained, however, is still lower than when using the conventional bottom-up approach.

2.2.2 Econometric Models

These models combine economic theory and statistical analysis for forecasting electricity demand, by establishing the relationships between energy consumption and the factors that influence it. When combined with end-use approach, the behavioural components are added to the end-use equations for more accurate forecasting and understanding of electricity consumption.

The most common econometric approach for end-use estimations is the conditional demand analysis (CDA) [31]. In a CDA applied to households, the total household consumption is the sum of consumption of various end-uses plus an error term or residual [32]. For an annual electricity consumption of end use j, for household i (X_{ij}, i=1……N), the following equation can be formulated: [31]

$$X_{ij} = \gamma_j + \sum_{m=1}^{M} \rho_{jm}\left(C_{im} - \bar{C}_{jm}\right) + \varepsilon_{ij} \qquad (1)$$

Where :

C_{im}= Household characteristics
$\bar{C}_{jm}$= Mean value of C_{im} variables for households possessing appliance *j*
γ_j= Mean value of electricity for appliance *j*
ε_{ij}= Stochastic error term

Widén, et al, proposed an stochastic Markov chain model with a bottom-up approach for modelling the electricity consumption in households in Sweden [33]. The proposed model defines that the electricity consumption depends on three factors: (1) the set of appliances in the household, (2) the individual electricity demand for these appliances and (3) the use of the appliances (behavioural factor).

The model presented in [33] worked satisfactorily when data from a combined survey of time use and electricity demand in Swedish households in 2007 (TU/EL-SEA-2007) was using for the validation process. Due to the similarity of the consumption patterns analysed, this model will be of great use for the development of the present model.

Table 1. Forecasting Methodologies comparison

Method	Advantages	Limitations	Authors
Trend	Easy data availability and fast processing of information is possible. Several commercial tools available.	Only suitable for short-term forecasting.	[10-15]
Similar Day	High short-term forecasting accuracy. Several computational tools (ANNs, Fuzzy, SVM, etc.) can be used	Forecasting accuracy decreases with increased time-span. Pre-processing of the data (training sets) has a strong impact on the model's performance.	[16-21]
End-Use	Suitable for long-term forecasting. Can simulate demand changes if new technologies are introduced or consumption patterns (e.g. energy efficiency programs) change.	Model's accuracy is highly dependent on the information from consumers the model is based upon. If the consumer's sample is too limited, the model cannot simulate large-scale demand forecasting	[10], [22-30]
Econometric	Suitable for long-term forecasting and simulation of different demand scenarios, technologies implementation, policy adoption and consumers' behavioural changes.	Historical electricity data, economic and behavioural components for the same consumers' population sample is required for building the model. Otherwise extrapolation is required and lowers the model's accuracy.	[31-33]

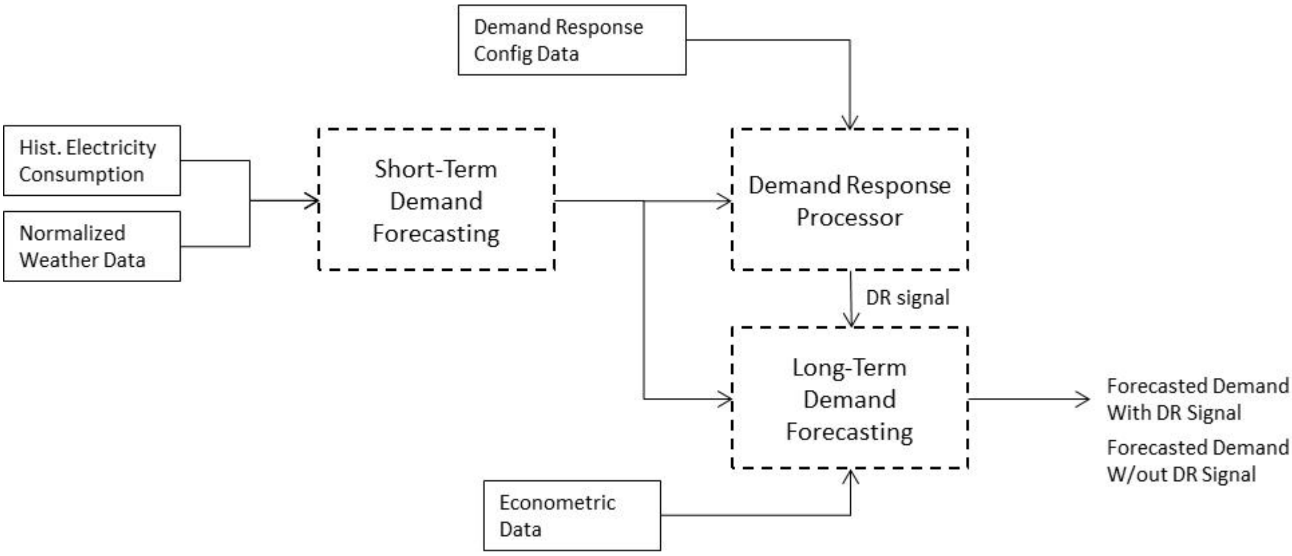

Figure 1. Proposed forecasting Model Structure

3. MODEL DESIGN

The model presented in [33] used the data from a pilot study of time use by Statistics Sweden (SCB) in 1996 for estimating the transition probabilities required in the Markov-chain model. For the present model, the data for a survey to be performed with 5000 households in the region of central region of Sweden is proposed in order to obtain more accurate demand-forecasting model, since more appliances are used now than they were in 1996.

Widen et al, model obtained adequate results when validated against the TU/EL-SEA-2007 data, the proposed model in this research is expected to obtain more accurate results due to higher-detailed consumer behaviour information and a larger validation data set.

3.1 Model Structure

The designed model uses the historical consumption data from the consumers´ the model is based upon, the historical weather data, econometric data from a survey and different demand response scenarios (e.g. time-of-use pricing) in order to forecast the demand consumption when the demand response signal is applied and the

3.1.1 Short-Term Forecasting Model

The short-term forecasting model uses the historical electricity consumption data from the utility operator Mälarenergi and the weather data from Meteonorm software for the studied area. From the given inputs, a short-term electricity load forecasting model is built in MATLAB using a 3-Layer Neural Network trained with the Levenburg-Marquardt algorithm. This forecasting model is limited to forecast hourly day-ahead demand.

3.1.2 Demand-Response Processor

The demand response processor is fed with different configuration data files to simulate DR scenarios: Time of Use pricing, automatic demand response, cooling and thermal loads switching etc. Based on the forecasted data from the short-term forecasting model, pre-defined thresholds trigger different DR signals. Each DR signal represents a different DR simulated scenario and it's fed into the long term-forecasting model

3.1.3 Long-Term Forecasting Model

The long-term forecasting model uses the data fed into the short-term forecasting model plus the econometric parameters obtained from the performed survey and the DR signal from the DR processor.

The long-term forecasting model is based on the markov-chain model proposed [33] and the model routines vary depending on the DR signal received, representing different demand response scenarios. The model outputs both the simulated demand with DR signal and the demand forecast without changes in the consumption behaviour, in order to evaluate de impact of each simulated scenario.

3.2 BEHAVIOURAL INFORMATION COLLECTING

The information collecting process uses a novel methodology for performing a large-scale quantitative evaluation of demand-response potential in a wide geographical area.

The first step performed was to deploy a large-scale questionnaire. This questionnaire was intended to gather information related to the users´ potential for consumer flexibility, evaluate consumers´ perception to different pricing scenarios, their interest in direct load control and to evaluate perception about different communication strategies for letting users know about demand response and energy use.

After the questionnaire gathering and process was finished, a new approach for performing an energy intervention scenario was addressed. Real-energy consumption data from the users´ smart meters and fictive flexible demand scenarios were tried with users in order to analyse their impact in a real-case scenario. These results will were compared with the results obtained from the forecasted data from the model in order to evaluate the impact of the simulated flexible demand scenarios.

4. CONCLUSION

In this paper an energy model design for short and long-term forecasting of electricity consumption for Sweden has been presented.

By combining several methodological approaches for short-term forecasting and applying a new strategy for gathering econometric and behavioural consumption patterns information, combined with real energy usage data, a more precise long-term forecasting model is expected.

The results of this model are suitable not just for prediction of electricity demand, but also for testing different policies and flexible demand strategies, otherwise not possible or with imprecise results. This strategy-testing process will be required in order to avoid high-prices peaks in the long-term for the Swedish electricity market.

Including real energy usage data in the model design opens new opportunities for up-scaling the model and builds an on-line electricity demand forecasting tool not just for short-term periods as it has been done in the past, but for long-term forecasting. In future developments, the model should adjust its parameters with real-time information using a feedback loop in order to increase its prediction accuracy.

This last approach and performance assessment of the working model will be discussed in future research papers.

ACKNOWLEDGEMENT

This work is supported by the Swedish Energy Agency. Special thanks to the Colombian´s national Science, Technology and Innovation administrative department, as well as the Tecnológica de Bolívar University for its financial support.

5. REFERENCES

[1] NordREG, “Nordic Market report 2011. Development in the Nordic Electricity Market,” 2011.

[2] E. Markets, “The Swedish electricity and natural gas markets 2010,” 2010.

[3] Elektrizitäts-Gesellschaft Laufenburg AG, “The Future Nordic Electricity Market: Power Flow Heading South - Prices North,” EGL RESEARCH EDITORIAL, 2006.

[4] NordREG, “NordREG report on the price peaks in the Nordic wholesale market during winter 2009-2010,” 2011.

[5] M. Bröckl, I. Vehviläinen, and E. Virtanen, “Examining and proposing measures to activate demand flexibility on the Nordic wholesale electricity market,” 2011.

[6] C. Bartusch, F. Wallin, M. Odlare, I. Vassileva, and L. Wester, “Introducing a demand-based electricity distribution tariff in the residential sector: Demand response and customer perception,” *Energy Policy*, vol. 39, no. 9, pp. 5008-5025, Jul. 2011.

[7] F. Wallin, *New opportunities provided by the Swedish electricity meter reform*, no. 82. School of Sustainable Development of Society and Technology, Mälardalen University, 2010.

[8] F. Wallin, C. Bartusch, E. Thorin, T. Bdckstrom, and E. Dahlquist, “The use of automatic meter readings for a demand-based tariff,” in *Transmission and Distribution Conference and Exhibition: Asia and Pacific, 2005 IEEE/PES*, 2005, pp. 1–6.

[9] M. Bollen and T. E. M. I. at the S. E. Agency, “Adapting Electricity Networks to a Sustainable Energy System – Smart metering and smart grids,” 2011.

[10] E. A. Feinberg and D. Genethliou, “Chapter 12: Load Forecasting,” in *Weather*, pp. 269-285.

[11] G. Bharadwaj Aarti and K. Meeta, *Demand Forecasting for Electricity: the Indian experience*. 2001, pp. 175-192.

[12] V. Richard, “Demand Shaping. Achieving and maintaining optimal supply-and-demand alignmen,” *Practice*. 2010.

[13] D. Neeley, A. Farrell, and J. Hornby, “Analytic Strategies for the Customer-Centric Utility,” *Intelligence*, no. June. 2011.

[14] SAS Institute Inc., “SAS ® Forecast Server - Fact Sheet.” SAS Institute Inc., 2011.

[15] H. Alfares and M. Nazeeruddin, “Electric load forecasting: Literature survey and classification of methods,” *International Journal of Systems Science*, vol. 33, no. 1, pp. 23-34, 2002.

[16] L. (Norwegian I. of S. and T. Pedersen, “Linda Pedersen Load Modelling of Buildings in Mixed Energy Distribution Systems,” Norwegian Institute of Science and Technology, NTNU, 2007.

[17] A. Al-Shareef and E. Mohamed, “One hour ahead load forecasting using artificial neural network for the western area of saudi arabia,” *International Journal of*, pp. 219-224, 2008.

[18] P. Mandal, T. Senjyu, N. Urasaki, and T. Funabashi, “A neural network based several-hour-ahead electric load forecasting using similar days approach,” *International Journal of Electrical Power & Energy Systems*, vol. 28, no. 6, pp. 367-373, Jul. 2006.

[19] A. Jain and M. Jain, “A novel hybrid method for short term load forecasting using fuzzy logic and particle swarm optimization,” *Power System Technology (*, 2010.

[20] X. Li, D. Gong, L. Li, and C. Sun, “Next day load forecasting using SVM,” *Advances in Neural Networks–ISNN 2005*, pp. 989–989, 2005.

[21] C. Chang-chun, “Support vector machines with similar day’s training sample application in short-term load forecasting,” *Electric Utility Deregulation and*, no. April, pp. 1221-1225, 2008.

[22] I. Vassileva, F. Wallin, and E. Dahlquist, “Analytical comparison between electricity consumption and behavioral characteristics of Swedish households in rented apartments,” *Applied Energy*, vol. 90, no. 1, pp. 182-188, Jun. 2011.

[23] R. Virve and L. Troels Fjordbak, “Creating Common Nordic Bottom-up Model for Household Electricity,” 2008.
[24] G.-yuan Lin, S.-chiang Lee, J. Y.-jen Hsu, and W.-rong Jih, “Applying Power Meters for Appliance Recognition on the Electric Panel,” *Design*, 2010.
[25] M. L. Marceau and R. Zmeureanu, “Nonintrusive load disaggregation computer program to estimate the energy consumption of major end uses in residential buildings,” *Energy Conversion and Management*, vol. 41, no. 13, pp. 1389-1403, Sep. 2000.
[26] G. Wood, “Dynamic energy-consumption indicators for domestic appliances: environment, behaviour and design,” *Energy and Buildings*, vol. 35, no. 8, pp. 821-841, Sep. 2003.
[27] A. Ruzzelli, C. Nicolas, A. Schoofs, and G. O’Hare, “Real-time recognition and profiling of appliances through a single electricity sensor,” in *Sensor Mesh and Ad Hoc Communications and Networks (SECON), 2010 7th Annual IEEE Communications Society Conference on*, 2010, pp. 1–9.
[28] J. Froehlich, E. Larson, S. Gupta, G. Cohn, M. Reynolds, and S. Patel, “Disaggregated End-Use Energy Sensing for the Smart Grid,” *Pervasive Computing, IEEE*, vol. 10, no. 1, pp. 28–39, 2011.
[29] G. W. Hart, “Nonintrusive appliance load monitoring,” *Proceedings of the IEEE*, vol. 80, no. 12, pp. 1870–1891, 1992.
[30] G.-Y. L. Chun-Nan Hsu, Jane Yung-Jen Hsu, “PAT (20110307200) Recognizing multiple appliance operating states using cirtuit-level electrical information,” 2011.
[31] B. M. Larsen and R. Nesbakken, “Household electricity end-use consumption: results from econometric and engineering models,” *Energy Economics*, vol. 26, no. 2, pp. 179-200, Mar. 2004.
[32] K. Tiedemann, “Using Conditional Demand Analysis To Estimate Residencial Energy Use and Energy Savings,” *Proceedings of the CDEEE*, pp. 1-5, 2007.
[33] J. Widén and E. Wäckelgård, “A high-resolution stochastic model of domestic activity patterns and electricity demand,” *Applied Energy*, vol. 87, no. 6, pp. 1880-1892, Jun. 2010.