Energy 48 (2012) 128–134

Contents lists available at SciVerse ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Prediction of appliances energy use in smart homes

Nicoleta Arghira [a,b,*], Lamis Hawarah [a], Stéphane Ploix [a], Mireille Jacomino [a]

[a] Laboratoire des Sciences pour la Conception, l'Optimisation et la Production de Grenoble, Grenoble Institute of Technology, France
[b] Department Automatic Control and Industrial Informatics, University Politehnica of Bucharest, Romania

ARTICLE INFO

Article history:
Received 31 October 2011
Received in revised form
28 March 2012
Accepted 3 April 2012
Available online 8 May 2012

Keywords:
Smart home
Prediction
Energy consumption
Stochastic process

ABSTRACT

This paper presents methods for prediction of energy consumption of different appliances in homes. The aim is to predict the next day electricity consumption for some services in homes. Historical data for a set of homes in France was used. Two basic predictors are tested and a stochastic based predictor is proposed. The performance of the predictors is studied and it shows that the proposed predictor gives better results than other approaches. Two processings are proposed to improve the performance of the predictor, segmentation and aggregation of data. Application results are provided.

1. Introduction

Energy consumption in the residential sector represents an important part of the total electricity demand. In this context, a proper prediction of energy demand in housing sector is very important. A bottom-up approach [1] can be used: first, the energy consumption prediction is done for each appliance in a home, then the forecast will be made for the total energy consumed in a home and, finally, a prediction can be made regarding the households supplied by a certain energy provider. Even if it is easier to predict overall consumption, it is important to be able to predict the consumption of each appliance because, regarding dynamic demand-side management, it is important to evaluate how much energy can be saved thanks to customers in case of unbalancing load. The energy savings depend on appliances: some can be unbalanced, some can be postponed and some cannot be changed.

The purpose of this paper is to predict the energy consumption in houses for the next 24 h, as the energy price in the day-ahead market is set for each hourly interval with one day advance. Also, the prediction of the next day energy consumption for different services in a house is an important part of a home automation system [2]. [3] presents a household energy control system with three layers: anticipative layer, reactive layer and device layer. The anticipative layer depicted in [2] is mainly concerned with the predictions of energy consumption.

Different methods for forecasting energy consumption in electrical grid were described in [4,5]. Short term energy prediction with support vector machines was presented in [6], but the energy consumption is considered at house level (all electrical appliances consumption). A prediction based on Bayesian Networks for a single appliance is considered in [7]. A statistical approach is further developed in this paper and a prediction algorithm based on an assessment index is proposed.

2. The need for energy prediction in housing

2.1. The smart grid

The concept of smart grid appeared as an answer to the new power system challenges. Smart grid integrates the use of sensors, communications, computational ability and control in order to enhance the overall functionality of the electric power system [8]. Smart grid initiatives seek to improve operations, maintenance and planning using modern technology in order to better manage energy use and costs [9]. Many governments sustain modern networks in the global context of energy saving and environment issues. United States Department of Energy has defined the functions required for smart grids in [10]: the ability to heal itself; to motivate consumers to actively participate in operations of the grid, to resist attack, to provide higher power quality, to accommodate all generation and storage options, to enable electricity markets to

* Corresponding author. Laboratoire des Sciences pour la Conception, l'Optimisation et la Production de Grenoble, Grenoble Institute of Technology, France.

E-mail addresses: arghira.nicoleta@gmail.com, nicoleta.arghira@aii.pub.ro (N. Arghira), lamis.hawarah@grenoble-inp.fr (L. Hawarah), stephane.ploix@grenoble-inp.fr (S. Ploix), mireille.jacomino@grenoble-inp.fr (M. Jacomino).

0360-5442/$ – see front matter
doi:10.1016/j.energy.2012.04.010

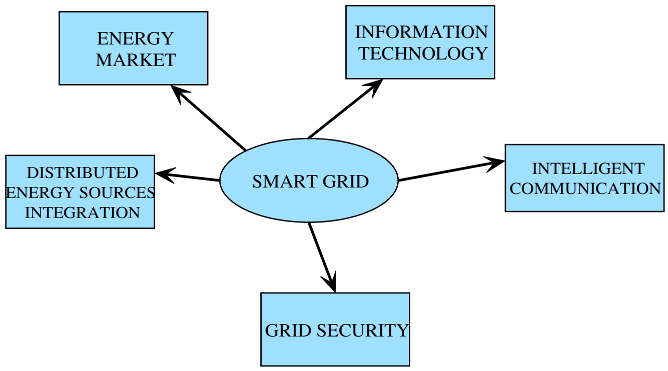

Fig. 1. The smart grid components.

flourish, to manage more efficiently the assets and costs. Fig. 1 depicts the important components of the smart grid.

The main purpose of the electrical grid is to assure the energy production necessary for consumers' consumption in a reliable manner. Now, with the smart grid demands, load management has been changing its objectives from load following to load shaping strategies. Direct load control, peak shifting, and various voluntary load management programs have been implemented by many utilities with varying degrees of success. Now, with the push for energy conservation and demand-side management as a key strategy for environmental compliance, demand response is taking on new realities.

Traditionally, demand response refers to the ability to cut off some electrical loads at peak times to ameliorate the need for peaking generation sources. Basically, it means being able to turn loads off on command. Progress in communication protocols and technology has been extraordinary in the past decade, making cheap, fast communication widespread. More and more electrical loads are equipped for communication as well as control. Also, a new concept is developed: demand dispatch. This refers to the ability to control in a precise manner the individual loads at all times, not only at peak period.

Load management involves two types of load control:

- Direct control;
- Control by cost.

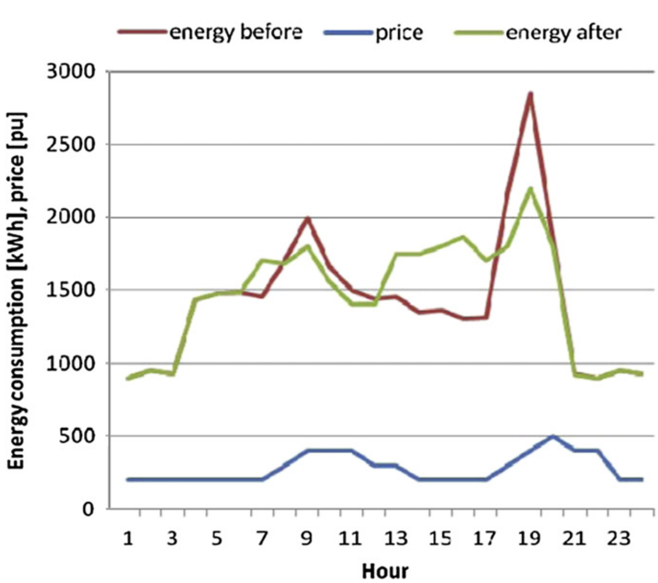

Fig. 2. The principle of control by cost.

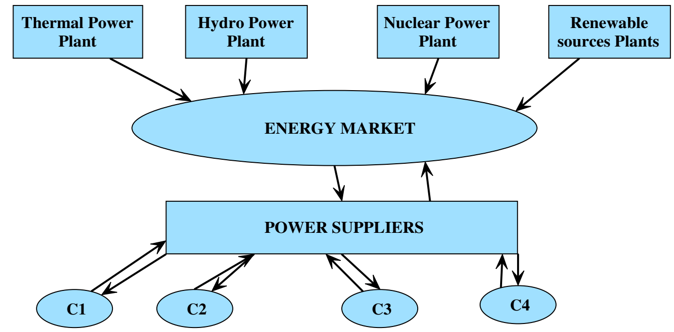

Fig. 3. Energy market in the power system.

Direct control refers to the classical methods of load control which involve increasing the energy production in case of higher load demand. The load frequency control in power systems is described in [11]. Considering the fact that energy resources are limited, there are many policies for energy saving on European and world scale. A good method to limit or change the energy consumption habits is the energy price. Fig. 2 shows the principle of cost control. In red is depicted the load curve for a house before cost control was applied. There are two energy consumption peaks during the day: in the morning, between 8 and 10 AM, and in the night, between 6 and 10 PM. The role of cost control is to change the load curve shape in such a way that energy consumption peak decreases, even though the total consumption for the specific household is the same. This mechanism involves increasing the prices for energy at peak periods and after these new tariffs are applied, the curve in green is obtained.

The energy market is a powerful instrument that sets the prices between the energy producers and energy suppliers and consumers (C1…C4), Fig. 3. It has an important role in the power system nowadays, but it is a complex bidding rules mechanism which sometimes is difficult to follow. The energy market is divided into different categories, but the Day Ahead Market or Spot Market is of great interest. This type of energy market involves bidding the energy consumption of the next day. It is a very complex mechanism, which requires a very good knowledge of the demand for the power suppliers. The participation in the day-ahead energy market imposes a dynamic energy management (hour by hour changes in the energy production/consumption ratio).

2.2. The importance of the energy prediction in smart grids

As seen in the previous section, the energy market is a key instrument in the smart grid. The power suppliers involved have to

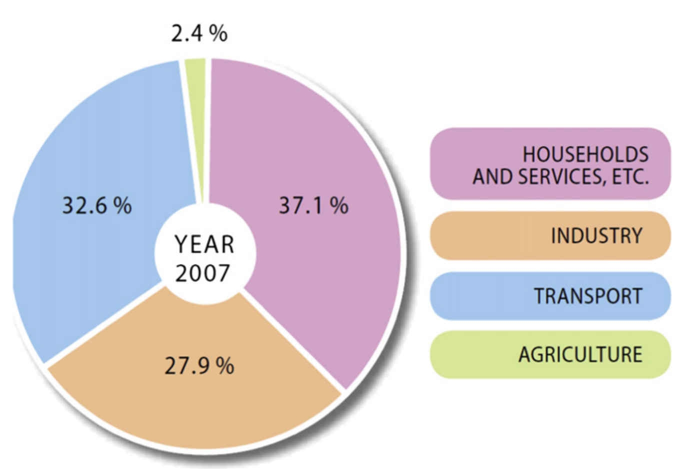

Fig. 4. Distribution of energy consumption by sector in the EU countries in 2007.

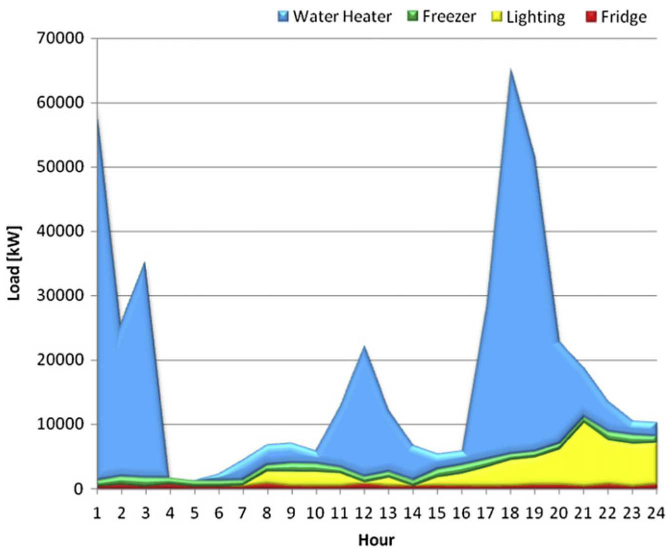

Fig. 5. Load curves for appliances in a house.

predict the next day consumption with good precision in order to obtain good prices for the traded energy. Since residential consumers represent a high percentage of the total energy consumption, the energy suppliers should focus on the forecasting the housing consumption. Fig. 4 shows the distribution of energy consumption by sector in the European Union countries in 2007 [12].

Predicting the energy consumption in the housing sector is a difficult task because it is depending on the users behaviour. Fig. 5 depicts the total load distribution by appliance in a house during a month.

The smart home is a new concept that allows control of the services in the house through a home automation system. The electrical devices include two-way communication capabilities for allowing the energy management system to control the consumption.

The smart home represents an important component in the smart grid. Fig. 6 shows the relationship between the smart home and the electrical grid. The solution in keeping a good energy management is to manage this type of load demand through price constraints.

In order to get a better load control, the energy prediction has to go down from total household energy consumption to electrical device consumption. There are different types of appliances: some can be unbalanced, some can be postponed and some cannot be changed.

Considering direct load control, it is essential to know the energy consumption in smart homes appliance by appliance in order to compute the energy reserve or to be able to stop certain services in case of higher energy demand.

When we consider the control by cost, prediction is also important. The home management system (e.g. in [13,14]) is very dependent on the forecast of prediction for the services in the house. This automatic system takes into account the optimal energy plan and decides the postponing of consumption for certain appliances. Also, a precise knowledge of the energy needs for the appliances that can not be delayed is necessary for computing the energy plan of the house at customer level and the energy forecast at the supplier level.

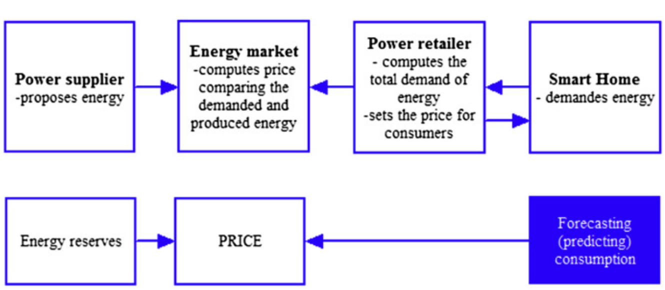

Fig. 6. Interaction between smart homes and smart grid.

3. Energy prediction methodology for appliances in homes

The objective of this work, energy prediction for appliances in homes, has a great influence in the functioning of a home energy management system. This system is able to determine the best energy assignment plan and a good compromise between energy production and energy consumption [2,3]. As seen in [3], it consists of an anticipative layer, a reactive layer and a device layer. The prediction of energy consumption of each electrical appliance in the house helps the anticipative layer to compute the optimal energy plan taking into account the user predicted requests and the available energy resources. It can decide to postpone some appliances or even to shut down some of them.

Different types of predictions can be made in order to determine the energy consumption of the appliances in a house. In this paper, the predictor aims at predicting whether the service will consume energy or not during each hour of the next 24 h.

The predictor performance is based on recorded data, which concern the energy consumption of appliances in 100 households in France during a full year. The used database comes from Residential Monitoring to Decrease Energy Use and Carbon Emissions in Europe (REMODECE), which is a European database on residential consumption, including Central and Eastern European Countries, as well as new European Countries (Bulgaria and Romania). This database stores the characterization of residential electricity consumption by end-user and by country. The information for each house is recorded each 10 min and concerns the energy consumption for the appliances and also the weather conditions (temperature, wind strength, wind direction, humidity).

3.1. Assessing the performance of predictors

Before designing a predictor, it is important to set up a method for assessing the performance of a predictor because it clarifies the

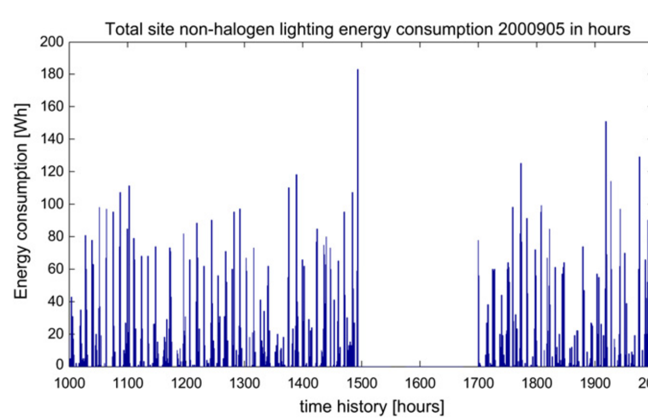

Fig. 7. Historical data for the energy consumption of non-halogen lighting in house 2000905.

objectives. For computing the performances of a predictor, test data are first to be considered. Because of the predictions required by an anticipative energy management system, the test data are the hourly energy consumption for an appliance over a full year. Fig. 7 shows a set of test data.

In order to evaluate the performance of predictors, some concepts have to be defined. Let h be the current hour and $e(h)$ be a binary value which is equal to 0 if the considered appliance is actually consuming energy during the hour h and 1 otherwise. Let $p_a(h)$ be a prediction provided by the predictor a, which is equal to 1 if the considered appliance is predicted as consuming power during the hour h and 0 otherwise. The precision of the predictor is then expressed by:

$$\pi_a(h) = \sum_{i=1}^{24} \frac{(25-i)|e(h+i) - p_a(h,h+24+i)|}{275} \quad (1)$$

The measurement of the precision gives more importance to the first predicted values. It follows the linear decrease shown in Fig. 8.

Any predictor a relies on an historical sliding time window of n hours used to predict the $d+1$ predictions. It can be denoted: $a^{h-n\to h}$. The number n has to be adjusted because if it is too large, seasonal phenomena may disappear, and if it is too short, data set will not be sufficient to yield a precise prediction.

The proposed algorithm for assessing a predictor a involves the following steps:

1. Set the time window dimension to n hours within the period for which the historical data was registered where n goes from 24 to 364 * 24;
2. Compute the predictions for the data corresponding to the historical sliding time window;
3. Compute the predictor precision $\pi_a(h)$ based on the "next day" data for all possible hours h and compute an average precision for the predictor.

3.2. Prediction with different predictors

3.2.1. The "will always consume" predictor

This type of predictor involves considering that the appliance will consume energy permanently. The prediction is computed based on a set of test data and refers to the probability of the service to consume energy. The prediction $p_a(h,h+24)$ is expressed:

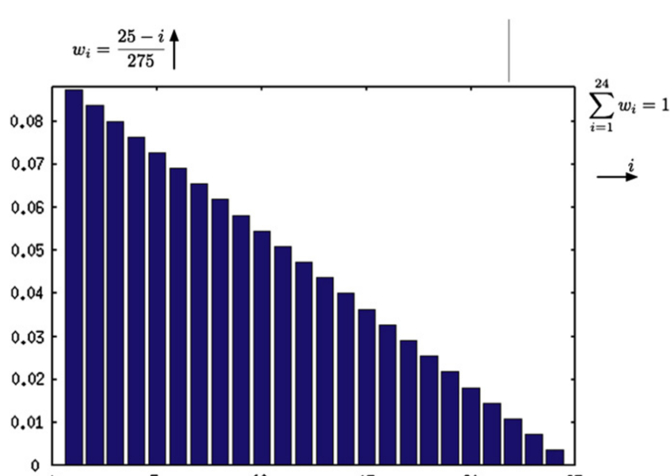

Fig. 8. Weights used to give more importance to short term predictions.

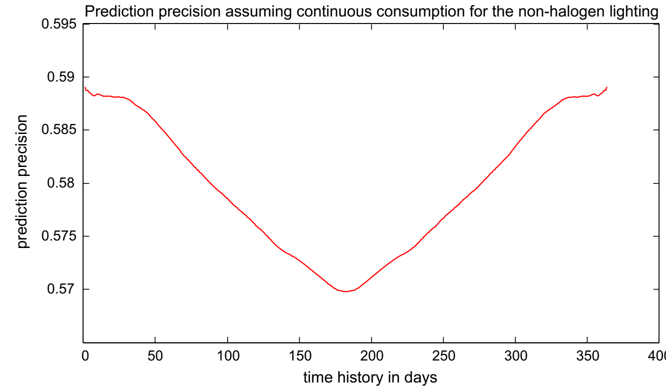

Fig. 9. Prediction precision assuming the service will consume continuously.

$$p_a(h,h+24) = 1, \quad h = \{1,2,...,24\} \quad (2)$$

Fig. 9 shows the prediction precision $\pi_a(h)$ for each time window of the test data considered in days (the prediction precision for a sliding window of 1 day, 2 days… etc.). This curve was obtained using the previously presented algorithm for assessing the predictor.

3.2.2. The "will never consume" predictor

This predictor assumes the service will not consume at all in the next day. The prediction is computed based on a set of test data and refers to the probability of the service not to consume). The prediction $p_a(h,h+24)$ is computed:

$$p_a(h,h+24) = 0, \quad h = \{1,2,...,24\} \quad (3)$$

It can be denoted that the value of precision for this predictor is the complement of the "will always consume" predictor precision. Fig. 10 shows the prediction precision for each time window of the test data considered in days for this predictor.

3.2.3. The ARMA predictor

The time-series approach is generally used in predicting energy consumption, as seen in [5]. One predictor that uses the ARMA (Auto Regressive Moving Average) method is described further. This method is one where the current value of a time variable is assumed to be a function of its past values and it is expressed as a weighted sum (moving average) [15]:

$$A(q)y(t) = C(q)e(t) \quad (4)$$

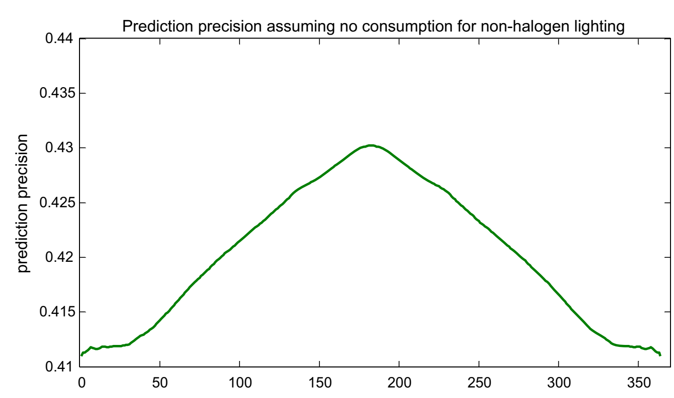

Fig. 10. Prediction probability assuming the service will never consume.

where A and C are polynomial functions in the time shift operator q^{-1}, $y(t)$ is the current output and $e(t)$ is the white noise (component used to account for uncertainty in the relationship and assumed to be identically distributed with zero mean and finite variance). The expressions of $A(q)$ and $C(q)$ are:

$$\begin{aligned} A(q) &= 1 + a_1 q^{-1} + a_2 q^{-2} + \ldots + a_{N_A} q^{-N_A}, N_A = \deg(A(q)) \\ C(q) &= 1 + c_1 q^{-1} + c_2 q^{-2} + \ldots + c_{N_C} q^{-N_C}, N_C = \deg(C(q)) \end{aligned} \tag{5}$$

The output value $y(t)$ is expressed as a weighted sum (moving average) of all past data $e(t)$ and its initial value $y(0)$:

$$y(t) = e(t) + \phi e(t-1) + \ldots + \phi^{t-2} e(2) + \phi^{t-1} e(1) + \phi^t y(0) \tag{6}$$

This ARMA model was used in order to predict the next day energy consumption and the result is depicted in Fig. 11:

The plot points out that this kind of modelling is not a proper way for predicting energy consumption in case of a singular appliance in a home. In this situation, a prediction that involves a probabilistic approach can be experienced.

3.2.4. The proposed predictor

An inhabitant in the house interacts with various electrical devices as part of his routine activities. Thus, energy consumption can be modeled as a stochastic process.

In this context, the proposed predictor specifies the probability of the appliance to consume on an hourly base. We consider the following prediction formula:

$$p_a(h,h+24) = \begin{cases} \dfrac{n_1(h,h+24)}{n(h)}, p_a\left(h,h+24\right) > p_{a,t} \\ 1 - \dfrac{n_1(h,h+24)}{n(h)}, p_a\left(h,h+24\right) \le p_{a,t} \end{cases}, h = \{1,2,\ldots,24\} \tag{7}$$

where $n(h)$ is the considered number of hours h in the test period, $n_1(h,h+24)$ is the number of times the service did consume during hour h of the historical data and $p_{a,t}$ is a set threshold. Fig. 12 shows the prediction precision of the proposed predictor related to the basic predictors in the previous subsections.

3.3. Improving the prediction precision

3.3.1. The segmentation of data

While mining the available data, some pattern of recurrence is searched in order to improve the prediction. A temporal segmentation can be used to introduce knowledge in the predictor, for instance, the use of the oven may be different for rainy Saturdays. The segmentation of data can be made considering different aspects such as the season, month, period of the day (day/night), type of day (weekday/weekend). The objective of this operation is to reduce the average dispersion in order to improve the prediction. After the segmentation is done, we will merge the segments that are similar using a clustering algorithm in order to gather the non-meaningful segments.

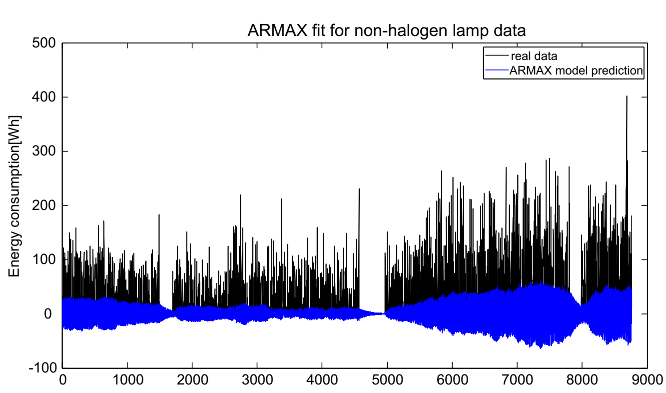

Fig. 11. ARMA fit for the test data.

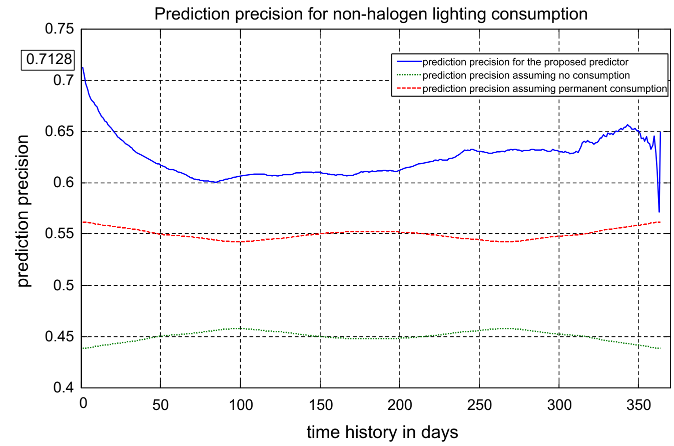

Fig. 12. Prediction precision for the proposed predictor.

A temporal segmentation, that considers each day of the week as a partition was done. For each segment, the hourly predictions are made considering the proposed predictor. A k-Means clustering algorithm is applied in order to group the similar consumption days.

The k-Means algorithm assumes a fixed number of clusters, specified in advance. Each cluster is defined by its cluster center and clustering proceeds by assigning each of the input data to the cluster with the closest centre. The grouping is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid. This algorithm is based on the euclidean distance:

$$\mathrm{ED}(X,Y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{8}$$

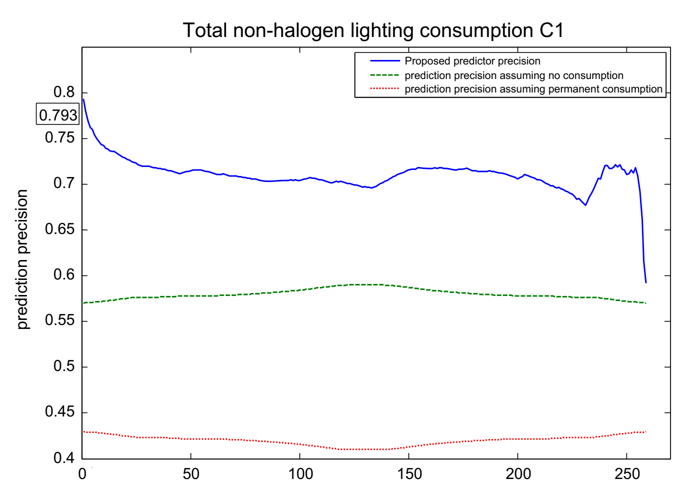

Fig. 13. Prediction precision comparison for the three predictors considering merged C1 data.

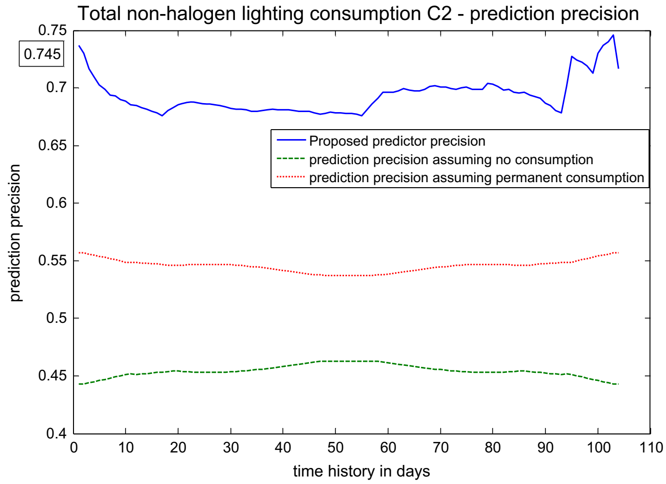

Fig. 14. Prediction precision comparison for the three predictors considering merged C2 data.

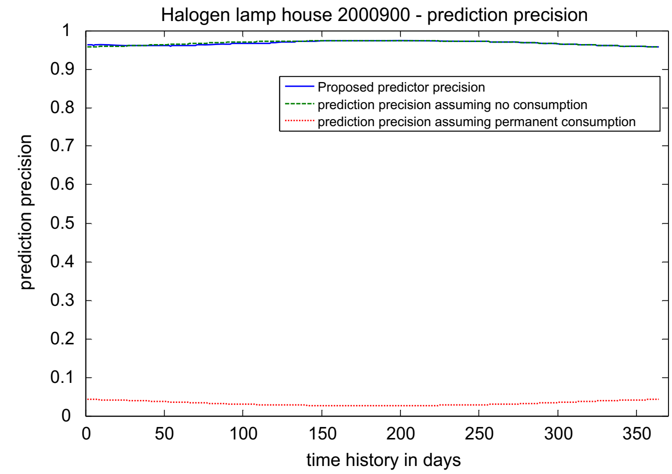

Fig. 16. The performance of the halogen lamp consumption prediction in house 2,000,900.

where X,Y are vectors, n is the vector length and x_i,y_i are their components.

The center of each cluster is then re-estimated as the centroid of the points assigned to it. The process is then iterated until a convergence criterion is accomplished:

$$\mathrm{ED}(X, Y) \leq \mathrm{ED}_t \tag{9}$$

where ED_t is an imposed threshold.

3.3.2. *The prediction precision after clustering*

After applying the iterative k-Means algorithm, two clusters are obtained. In the presented case, cluster C_1 groups weekdays data and cluster C_2 gathers Saturday and Sunday data. After the clusters are obtained, the initial data corresponding to the energy consumption is divided into 2 sets according to the number of clusters and the considered segments. The predictor in Section 4 is then applied in order to get the prediction precision. Figs. 13 and 14 show the prediction precision for the new test data. The blue curve represents the precision for the proposed predictor and the other two are the curves for the basic predictors.

Figs. 12–14 present the prediction precision in 3 situations: for initial energy consumption data, for merged segments in cluster C1 data and for merged segments in cluster C2 data. When comparing the obtained curves for the proposed predictor, the precision of the predictor increases after the clustering is applied. This proves that the segmentation of data and then the merging of similar partitions is a good method for increasing the prediction performance.

4. Global study of the services in the house

This section presents the results for different electrical appliances in the house when the proposed predictor is used in comparison with the basic predictors “will never consume” and “will consume continuously”.

The prediction precision is computed as explained in Section 3 for a sliding time window between 1 and 364 days, covering all the historical data available.

The global study of the different appliances in houses shows that the prediction acts in a special manner depending on the type of the electrical appliance. The prediction precision for the refrigerator (Fig. 15) or the freezer (Fig. 17) is lower than the precision assuming permanent consumption for time windows higher than 14 days. This implies that the prediction for these appliances should be done considering a short period of historical data (e.g. two weeks) in order to get a high performance. This conclusion was expected since the energy consumption for these appliances is dependent on the season, so a short period of time is significant for prediction. The

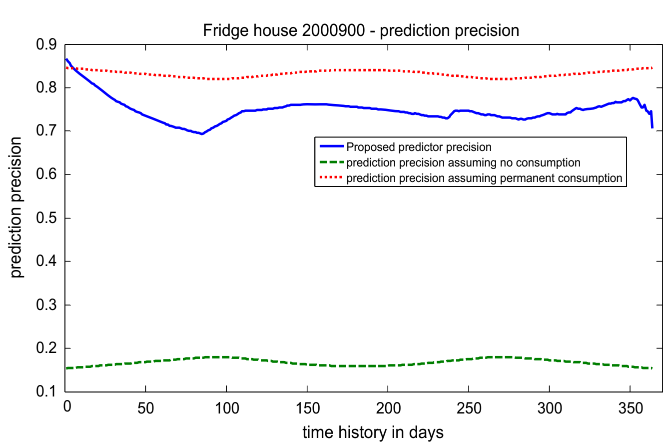

Fig. 15. The precision of the refrigerator consumption prediction in house 2,000,900.

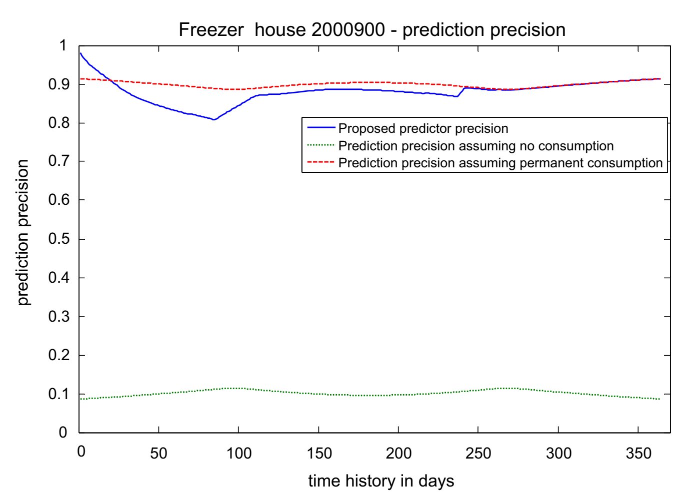

Fig. 17. The precision of the freezer consumption prediction in house 2,000,900.

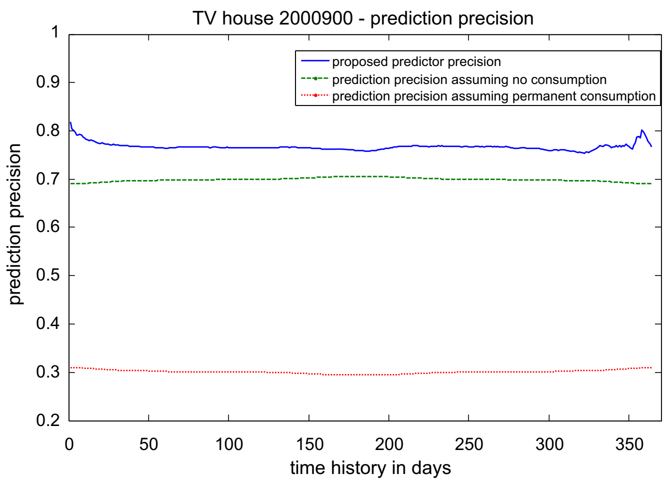

Fig. 18. The precision of the TV consumption prediction in house 2,000,900.

performance of prediction for the TV or non-halogen lighting is higher than the performance of the basic predictors for the entire recorded data interval (Figs. 16 and 18).

5. Conclusion

Forecasting the energy consumption in homes is an important aspect in the power management of the grid, as the consumption in the residential sector represents a significant percentage in the total electricity demand. The development of the smart grid is not possible without a good prediction of energy consumption. The trend nowadays is to get the prediction of energy consumption not only at house level, but at household appliance level.

The prediction of energy consumption in housing is very dependent on inhabitants' behavior, so a stochastic method for prediction has been presented in this paper. The paper discusses about how to evaluate the precision of a predictor in the day + 1 power management context. Different basic predictors are presented and tested for the available historical data. A relevant predictor is presented. It is based on the segmentation of data considering the patterns in energy consumption. The historical data is divided according to the results of the k-means clustering algorithm. This procedure improves the precision of the predictor.

Further work involves testing the proposed predictor for all the appliances in a house in order to decide the proper way for prediction at the equipment level.

References

[1] Iliescu SSt, Fagarasan Ioana, Pupaza D. Analiza de sistem si informatica industriala. Bucuresti: AGIR; 2006.
[2] Long Ha D, Ploix S, Zamai E, Jacomino M. Realtimes dynamic optimization for demand-side load management. International Journal of Management Science and Engineering Management 2008;3(No. 4):243–52. ISSN 1750-9653, England.
[3] Abras S, Ploix S, Pesty S, Jacomino M. An anticipation mechanism for power management in a smart home using multi-agent systems. In: Proceedings of the IEEE 3rd international conference on information and communication technologies: from theory to applications; 2008. p. 110–6. Syria.
[4] Alfares KH, Nazeeruddin M. Electric load forecasting: literature survey and classification of methods. International Journal of Systems Science 2002;33-(number 1):23–34. ISSN 1464-5319.
[5] Feinberg EA, Genethliou D. Load forecasting, applied mathematics for restructured electric power systems. SpringerLink; 2005:269–85. doi:10.1007/0-387-23471-3_12.
[6] Jain A, Satish B. Clustering based short term load forecasting using support vector machines. In: Proceedings of 2009 IEEE Bucharest PowerTech; 2009. Bucharest, Romania.
[7] Hawarah L, Ploix S, Jacomino M. User behavior prediction in energy consumption in housing using Bayesian networks, lecture notes in computer science. SpringerLink 2010;6113:372–9. doi:10.1007/978-3-642-13208-7_47.
[8] Gellings Clark W. The smart grid: enabling energy efficiency and demand response. ISBN 0-88173-624-4, USA; 2009.
[9] Ipakchi A, Albuyeh F. Grid of the future. IEEE Power and Energy Magazine 2009;8(3):20–9. Digital Object Identifier 10.1109/MPE.2008.931384, ISSN 1540-7977.
[10] National Energy Technology Laboratory (NETL). A vision for the modern grid; 2007.
[11] Arghira N, Dumitru I, FăgărăŞan I, Iliescu SSt, Soare C. Load frequency regulation in power systems. In: Proceedings of 2010 international conference on automation, quality and testing, robotics;, ISBN 978-1-4244-6722-8; 2010. p. 94–9. Cluj, Romania.
[12] EU energy and transport in figures statistical pocket book 2010;, ISBN 978-92-79-13815-7; 2010. Belgium.
[13] Abras S, Ploix S, Pesty S, Jacomino M. A multi-agent design for a home automation system dedicated to power management. In: Proceedings of the IFIP conference on artificial intelligence applications and innovations; 2007. Greece.
[14] Warkozek G, Jacomino M, Ploix S, Wurtz F. Generic formulation of optimization problems for energy management: solving difficulties, practical and mathematical analysis. In: Proceedings of the 8th international symposium on electric and magnetic fields; 2009.
[15] Tham MT. Dynamic models for controller design – lecture notes. UK: New Castle; 2009.