Short term electricity forecasting using smart meter data

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***Abstract*— Smart metering is a quite new topic that has grown in importance all over the world and it appears to be a remedy for rising prices of electricity. Forecasting electricity usage is an important task to provide intelligence to the smart gird. Accurate forecasting will enable a utility provider to plan the resources and also to take control actions to balance the electricity supply and demand. The customers will benefit from metering solutions through greater understanding of their own energy consumption and future projections, allowing them to better manage costs of their usage. In this proof of concept paper, our contribution is the proposal for accurate short term electricity load forecasting for 24 hours ahead, not on the aggregate but on the individual household level.**

Keywords— smart metering, short term energy forecasting, neural networks, forecast accuracy

I. Introduction

Smart metering systems are expected to play important role in reducing overall energy consumption and increasing energy awareness of the users. One of the most important aims of smart metering is to encourage users to use less electricity through being better informed about their consumption patterns. Leveraging smart metering to support energy efficiency on the individual user level poses novel research challenges in monitoring usage and providing accurate load forecasting.

Load forecasting on the individual household level is challenging task due to the extreme system volatility as the result of a dynamic processes composed of many individual components. The individual load profile is influenced by a number of factors, such as devices' operational characteristics, users' behaviours, economic factors, time of the day, day of the week, holidays, weather conditions, geographic patterns and random effects. With the appearance of novel technologies, demand response programs, changes in the lifestyle and energy consumption pattern etc., it becomes necessary to use alternative modelling techniques, to capture the factors responsible for accurate short term forecasting in smart metering applications.

In this paper, we will study an approach to forecast the hourly electricity loads of a particular individual consumer for 24 hours ahead. However, it should be noted that forecasting loads of individual smart meter is not common practice since the volatility of the system is high thus resulting in high error rates.

II. Modelling method

Several modelling techniques are typically used for energy load forecasting. These techniques can be classified into nine categories [1]: (1) multiple regression, (2) exponential smoothing, (3) iterative reweighted least-squares, (4) adaptive load forecasting, (5) stochastic time series, (6) ARMAX models based on genetic algorithms, (7) fuzzy logic, (8) artificial neural networks and (9) expert systems.

Based on literature findings we can conclude that time series analysis techniques are neither scalable to higher dimension nor are effective in highly volatile data [2]. For this reason time series methods such as regression models, ARIMA models, GARCH and hybrid models such as combination of ARIMA and GARCH using wavelet transform are not considered for short term forecasting [3,4].

In comparison to the above mentioned there are techniques such as artificial neural networks, which, through their hidden layers and ability to learn, seem much more capable of solving forecasting problem. This technique is able to identify hidden trends thereby finding the trends in time series and use them to produce the forecast.

III. Smart metring data

Electricity measurements data were prepared using Mieo HA104 meter installed in one of the households in Warsaw, Poland for the purpose of SMEPI project (project aimed to develop smart metering solutions, partially financed by National Centre for Research and Development (NCBiR)). The household consisted of two adult people and a child. The household was living in a flat and was equipped in various home appliances including washing machine, refrigerator, dishwasher, iron, electric oven, two TV sets, audio set, pot, coffee maker, desk lamps, computer, and a couple of light bulbs. The data were gathered during 60 days, starting from 29 August until 27 October 2012.

Original dataset contains the electricity usage readings of the smart meter at every second, every minute and every hour. From these readings, we extracted the hour loads (in kWh) for the purpose of short-term load forecasting. Data characteristics over the time are illustrated in Fig. 1.

In our research, we focused on forecasting the electricity usage of a particular household for 24 hours ahead. In order to forecast the load we constructed a feature vector with such attributes as: load of previous 24 hours, maximum, minimum, range and average load of previous hours, day of the week and finally temperature observed in each hour.

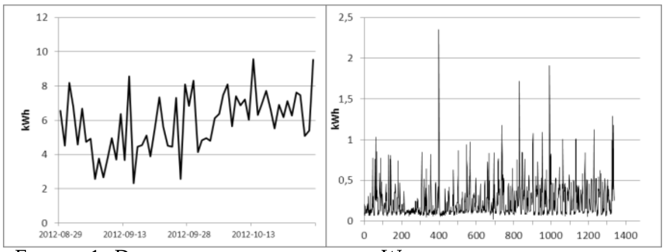

FIGURE. 1. DAILY AND HOURLY LOAD IN KWH.

IV. FORECASTING EXPERIMENT

To assess the model performance for forecasting, we used two measures: precision and accuracy [4]. Traditional measures such as percentage error are not considered as the most appropriate for the forecasts prepared on low granulation data as they can be highly over-influenced by some very bad instances and can overshadow quite good forecasts.

Precision is the measure of how close the model is able to forecast to the actual load. To measure precision we used mean squared error (MSE).

Accuracy is the measure of how many correct forecasts the model makes, where the term *correctness* is defined by user. This can be done by defining correct forecast as the value within a percentage range of the actual load. However, for low loads, a percentage range may become insignificant. For a load of 0.1 kWh, a 10% range would be 0.09–1.10 and a forecast of 0.2 kWh will be considered as wrong, but in practice such forecast would be acceptable. To overcome this false loss of accuracy we set two scales to measure accuracy. We set a 10% range of error for accuracy, but if the load is smaller than 1 then we consider range of ±0.10 kWh as range of acceptable forecast. Therefore, accuracy for hour i is given as:

$$AC = \sum 1\{W_{hi} > 1 \,\&\, |W_{hi} - P_{hi}| < P_{hi} \times 0.10\} + \sum 1\{W_{hi} < 1 \,\&\, |W_{hi} - P_{hi}| < 0.10\}, \quad (1)$$

where W_{hi} is the observed load in hour i and P_{hi} is the forecasted load in hour i.

Before estimating and assessing the MLP network model, we have randomly selected two samples. The calibration sample contained 80% of the observations and the test sample contained 20% of the observations. A three layer back propagation neural networks were trained on the data. As loss function we chose the least squares estimator.

For training neural networks we used the BFGS (Broyden-Fletcher-Goldfarb-Shanno) algorithm, which belongs to the broad family of quasi-Newton optimization methods. This method performed significantly better than for instance traditional algorithms such as gradient descent, but it was more memory and computationally demanding.

In the experiment we tried several neural network structures to get the best result. As a result we received neural network with input layer consisting of 49 perceptrons which were activated by hyperbolic tangent function; hidden layer consisting of 38 perceptrons and finally, the output layer consisting of 24 perceptrons which were activated by logistic function. Each of 24 perceptrons represented the single hour forecast. The final results obtained by neural network and aggregated over all hours are shown in Table 1.

TABLE I. MODEL RESULTS AGGREGATED OVER ALL HOURS.

Set	Accuracy (%)	MSE
Training	65	0.09
Test	62	0.10

For training sample, the accuracy which measures of how many correct forecasts the model makes is 65% and the precision of how close the model is able to forecast to the actual load (MSE) is 0.09. The results associated with the test set are close to these obtained on training set. For this sample ANN obtained 62% of accuracy and 0.10 for MSE.

Additionally, to give also a graphical view on the performance of the proposed forecast for day-ahead in particular household, the results obtained for the two randomly test days, are shown in Fig. 2. From this figure we can observe that the load forecast curve follows the real load curve. The trend is followed well enough but as it was expected, due to household behaviour and other immeasurable influences, there are some deviations when comparing these two curves.

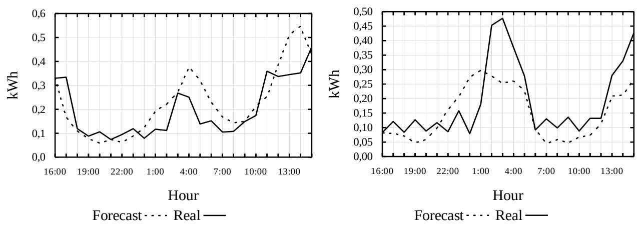

FIGURE. 2. HOURLY FORECASTS VS REAL LOAD.

V. CONCLUSIONS

In this paper, we presented a proof of concept to forecast electricity load on individual level data, what can potentially provide greater intelligence to the smart meters. The result of MLP network model used for 24 hours ahead short term load forecast shows that neural network has a good performance and reasonable prediction accuracy was achieved.

ACKNOWLEDGMENT

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REFERENCES

[1] H.K Alfares., M. Nazeeruddin, ”Electric load forecasting: literature survey and classification of methods”, *International Journal of Systems Science*, vol. 33(1), pp. 23–34, 2002.

[2] G.E.P Box., G.M Jenkins, *Time series analysis. Forecasting and control*, Englewood Cliffs, NJ, Prentice-Hall, 1994.

[3] Z. Aung, J. Williams, A. Sanchez, M. Toukhy, S. Herrero, ”Towards Accurate Electricity Load Forecasting in Smart Grids”, *Proc. of the 4th Int. Conference on Advances in Databases, Knowledge, and Data Applications*, DBKDA, St. Gilles, Reunion Island, pp. 51-57, 2012.

[4] F. Javed, N. Arshad, F. Wallin, I. Vassileva, E. Dahlquist, ”Forecasting for demand response in smart grids: an analysis on use of anthropologic and structural data and short term multiple loads forecasting”, *Applied Energy*, vol. 69, pp. 15-160, 2012.