

LOAD FORECASTING IN A SMART GRID ORIENTED BUILDING

Satya Ram TWANABASU

Østfold University College - Norway

satyart@hiof.no

Bernt A. BREMDAL

Narvik University College & NCE Smart Energy Markets - Norway

bernt@xaliance.com

ABSTRACT

This research work has addressed demand side flexibility in a smart grid oriented building. The principal purpose has been to build a short term forecasting model that will predict the next hour consumption. Three advanced methods of forecasting have been investigated for this purpose, the ARIMA (Autoregressive Integrated Moving Average) model, Artificial Neural Networks (ANN) and Support Vector Machines (SVM). Historic time series of loads and consumption data of Østfold University College in Halden have been used for seeding and tested for trends, seasonality, cyclic characteristics and randomness. Accuracy for all three methods are fair and can be applied for the purpose. Priority is placed on ARIMA due to its transparency. This provides a simple form of explanation. The next hour predictions obtained will yield sufficient information and latitude to change operational strategies and move loads or substitute imported electricity with energy produced from local resources.

INTRODUCTION

The work reported here was associated with the research projects 'IMPROSUME' and 'Manage Smart in Smart Grid (MSISG)' initiated by NCE Smart Energy Market. The former looks at the role of the prosumer in the energy market and the latter addresses primarily energy efficiency in the context of smart grids and AMS. Common to both is the focus on user flexibility. Understanding user behaviour and tolerances with respect to temperature, indoor climate and mobility constitute important parts of this. Østfold University College in Halden (HIOF), Norway has been used as a test site to study the concepts developed in these projects.

A general optimization model for the consumers flexibility based on stochastic programming is part of the MSISG and described in [4]. The proposed model optimizes the use of energy for a given period, provided that the different types of state information representing the demand side and supply side can be fused and processed. Besides know-how about the user side, information about the energy consumption is essential. The predicted values combined with the price information that reflects the state of the energy market can be used for real time control and planning to yield efficient energy management. Thus, the research presented has addressed demand side flexibility whereby consumption values are predicted to yield a "look ahead" and thereby cater for a more optimal control strategy.

It is anticipated that prosumers will play an important role

in the future energy market dominated by a Smart Grid regime. Prosumers are users of energy that resonate with the market both as consumers and producers [1]. The research conducted has addressed HIOF in Halden as a future prosumer using its premises as its primary asset. Essential to this is how to exploit the latent user flexibility. Ottesen [2] describes 5 forms of operational user flexibility schemes that can be exploited. Most pertinent to the work reported here is electricity load reduction and fuel substitution. By predicting the next peak load based on history, it is possible to make up-front measures to avoid excessive peaks. It may also help to determine strategies for substituting imported electricity with local supplies or reduce the loads by simply suspending heating or delay CO₂ flushing [3]. Today local supplies consist of oil and an oil heated boiler. In the future this could be made up of renewable sources with a storage capacity i.e. solar panels or remote heating facilities. Execution of such strategies will depend on the state of the grid, looming "brown outs", net tariffs and market prices. Although the literatures [6] to [8] have laid ample background on the domain of load forecasting, the forecasting models in our context have been explored to pursue user flexibility. A proper determination of the energy usage in the building has been done thorough the heat transfer function to compensate the energy used in the heating boilers. Furthermore, a thorough analysis has been performed to ascertain the effect of ambient temperature on the energy consumption profile that has resulted in a noisy and quite fluctuating dataset.

The paper is organized as follows. In the next section, we describe the dataset. The experimental methods and results are provided in following session. Finally, we conclude this paper discussing the overall findings of the work done.

DATA DESCRIPTION

The dataset encompasses load profiles and energy consumption for HIOF in Halden. The area has a comparatively mild climate. However, during the winter time from November to February, days with temperature of -17°C are not uncommon. Historic hourly data sampled from the control centre of the building during a period from 2008 to 2010 have been used for seeding. It has also been tested for trends, seasonality, cyclic characteristics and randomness. Besides these consumption values, the hourly temperature values measured from the nearest weather station have also been used. Similarly, the holidays during that period have been considered. As the dataset is a product of the energy management system in the building, an overview of the energy usage and the energy measurement system implemented the building has been provided.

Energy Usage in the Building

The energy consumed at the HIOF campus is primarily used for heating, lights and air conditioning. Appliance oriented energy use is also significant. However, basic temperature control and heating of fresh air amounts to the biggest loads. In most zones set point for temperature control lies between 21 to 22°C. As the temperature outside has a direct effect on the energy needed to warm up the building, some degree of correlation between the temperature and the energy consumption is expected which is explained in the following sub-section. The process of heating the building is performed by means of a water boiler which today is operated either with electricity or with oil but not with both sources at the same time. The owner of the building takes a decision to operate the water boiler either on oil or on electricity for the whole week.

Energy Measurement in the Building

The measurement of electricity in the building has been done through four Kamstrup 351B smart meters dedicated to four different zones of the building. However, there is not any direct means of measuring the energy usage during the oil usage period of the building. To quantify correctly the energy usage in such period, heating transfer functions were developed.

Data Analysis

Data analysis and visualization can uncover quite useful information that might guide the experimentation. So, a data analysis technique based on exploratory data analysis has been adopted. Presented here are some notable observations about the dataset.

Properties of Load Demand

The consumption data showed some seasonal pattern with higher demand in the winter than in the summer; it depicts the relation between load and weather conditions. Probing further, weekly load patterns were observed. Demand in weekend is lower than those during weekdays. A more detailed examination revealed a daily pattern showing the higher loads during the office hours than those in non-office hours.

Table 1 depicts the scatterness of the hourly consumption data. Having the Standard deviation of 429.KWh and mean of 798.8kWh, these values vary in a wide range of 133kWh to 4252 kWh. This has made the task of prediction difficult.

Table 1 Summary of Consumption

Mean	Max	Min	S.D.
798.8KWh	4252 KWh	133 KWh	429.1 KWh

Temperature Variation

Due to the geographical location of the college, the temperature showed a wide variation in the range of -17°C to 27°C as tabulated below. The minimum temperature was

found to be -17°C occurring twice on 2010-01-09 (2AM) and 2010-12-22 (5AM). The maximum temperature was found to be 29°C occurring on 2008-07-25(3PM). The S.D. of 8.075°C suppressing the mean of 7.461°C indicates scatter-ness of temperature values.

Table 2 Summary of Temperature

Mean	Max	Min	S.D.
7.5°C	29°C	-17°C	8.1°C

As a result, the load demand shows some seasonality and hence a moderately strong correlation coefficient of -0.69 has been observed in our case.

METHODS

ARIMA

The most fundamental time series models are the autoregressive model and the moving average model. Autoregressive models are based on the idea that current values of the series x_t can be expressed as a function of past values. In moving average model, it is assumed that the white noise w_t are linearly combined to form the observed data. ARMA (Autoregressive Moving Average) is a more general model which is the combination of autoregressive model and moving average model. To process non-stationary process, we can extend the class of ARMA model to include differencing. Such extended model is called Autoregressive Integrated Moving Average (ARIMA). ARIMA model encompassing seasonality is called Seasonal ARIMA.

There are various models for such analysis and are influenced by the work of Box and Jenkins [10]. Readers are referred to [11] for the detailed mathematics. Such methods used to dominate the load forecasting scenarios. Good references for such literatures can be obtained from [11]. As the forecasting of any system essentially deals with the correlation of historical data, the application of time series analysis methods is quite appealing and convincing. So, we have chosen this established method as the starting point of our experimentation.

ANN

Artificial Neural Network (ANN) is a machine learning technique inspired by the biological learning system, particularly the functioning of the human brain. Due to their strong ability to generalize from experience and to cope with noisy data, they are being used in a wide variety of tasks in different fields of business, industry and science. Various neural network architectures have been used for time series forecasting. Some of the representative literatures on their use in load forecasting listed in [11]. ANN can be broadly divided into static and dynamic neural network. Static networks are the feed forward networks

which do not have any delays and any temporal feedback elements. The output in such network is resulted directly from the input through feed forward connections. For a network to be dynamic, it must be provided with any short term or long term memory unit. So, the output of such network depends not only in the current input to the network, but also on the previous inputs, outputs and states of the network.

Focused Time Delay Neural Network (FTDNN) is one of the most fundamental dynamic networks consisting of a short term memory unit which can be simplified merely into an equivalent static network. One of such techniques is *unfolding-in-time* [5]. Some literatures have treated the model of Constrained Static Network as sliding window technique as it includes the N-tuple input sliding over the full training set. The notion of Constrained Static Network can be expanded further to include exogenous features that affect the prediction. Mathematically, it can be expressed as: $x(t+d)=f(y(t),ex_1(t),\dots,ex_m(t))$, where, $y(t)$ is the $N - \text{ary}$ vector of lagged x values and $ex_i(t)$ is a vector of exogenous variables. Since such models are quite suitable for time series prediction as in our context; we have used them with some of the fastest training algorithms.

SVM

Support Vector Machines (SVMs) are a set of related supervised learning techniques originated from the statistical learning theory. SVM is a blend of linear modeling and instance based learning. It was invented by Vepnik and Cotes [11] and it applies a simple linear method to the data in a high-dimensional feature space. More precisely, it uses hypothesis space of linear functions in a high dimensional feature space and is trained with a learning algorithm based on optimization theory. SVMs essentially consist of two components namely – kernel and optimizer algorithm. Kernel divides non-linear data into high-dimensional space and makes the data linearly separable [11]. The learning takes place in the feature space, and the data points only appear inside dot products with other points. The second component of SVM namely, the optimizer algorithm is applied to solve the optimization problem. For the detailed mathematical treatment of SVM, the readers are referred to [11]. SVM are relatively advanced machine learning techniques. Literatures listed in [11] in this domain have found it better than earlier methods. So, we have used this method to improve the accuracy of the prediction.

EXPERIMENTS

Regardless of different techniques that have been applied for prediction, some common denominators have been set to compare the results of experimentations. In each session, the dataset has been divided into 70% training and 30% testing. The Mean Absolute Percentage Error (MAPE) and

the Root Mean Squared Error (RMSE) on test set are calculated. Finally, the comparison of the models is done on the basis of MAPE values.

We began our experimentation with Seasonal ARIMA. All major steps (model selection, parameter estimation and model diagnosis) as specified by Box and Jenkins [9] were performed with the seasonality of 24 hours depicted by the ACF (Auto-Correlation) and PACF (Partial Autocorrelation Function). After the model selection phase, the parameter estimation, based on the maximum likelihood estimation method, was performed. Finally, the model diagnosis was performed based on the residual analysis with out-of-sample approach. The result obtained with such approach is summarized in Table 3. The model is expressed mathematically through the usual notation of x_t , w_t and B representing time series data, white noise and Backshift operator respectively.

Table 3 Result of ARIMA model

Model	MAPE	RMSE
$(1-B^{24})(1-B)x_t=(1-0.93B^{24})(1-0.86B-0.14B^2)w_t$	5.67%	99

The next session was carried out with ANN. Beginning with a simple configuration and moving toward complex ones, we ran the datasets five times for each configuration. Then, we adopted ‘The Best of Five’ approach to select the best result with window size of 12 and 24. Besides the historical values, we inputted exogenous components like year, month, DayOfWeek, WorkingDay, Hours, next hour temperature forecast, min, max and average temperature of last n hours. Using the sigmoid log function at the hidden layer and linear function at the output layer, the network was trained with Levenberg-Marquardt algorithm. The best result was obtained with a window size of 24 and 7 nodes at the hidden layer as shown in Table 4.

Table 4 Best Result of ANN

ANN Model	MAPE	RMSE
logsig,purelin,trainlm,7	5.319%	85.803

Finally, the SVM was used in the third session. Just as in previous session, we included the historical values as well as the exogenous variables. A manual tuning of optimum values namely, the gamma values and cost values was performed. The tuned values resulted in the best SVM model with the performance summarized in Table 5.

Table 5 Best Result of SVM

SVM Model	MAPE	RMSE
Method='nu-regression',kernel='radial',cost=2.0,gamma=4.0	7.682%	96.789

DISCUSSION AND CONCLUSION

The application of a well-established statistical approach and two machine learning techniques in the HIOF case resulted in three prediction models with test accuracies 5.3 - 7.6%; the ANN standing superior to the other two. The accuracies obtained are encouraging considering the dataset spans a shorter period than [6]. However the dataset is richer and includes temperature. We assume that this has made a positive contribution, although further analysis needs to be conducted in order to establish this firmly. Regarding the practical implementation, the ARIMA holds a greater potential in the context described here because of its transparency. ANN poses some challenges in reproducibility due to its 'black-box' like learning approach, random weight initialization and complex training algorithm. The difference in prediction error between the ARIMA and ANN technique yields marginal effects within the context described here. Increased transparency introduces an element of explanation that can help to support the empiricism involved. All three methods have been applied for many purposes across different domains. There is no uniform measure of quality across these simply because accuracy first of all depends on data quality. However, what we have shown here is that prediction of consumption is possible and it will yield practical effects and cater for increased energy effectiveness. We will apply ARIMA for look-ahead to plan demand side strategies with respect to external grid and price signals at the campus described. 5-7% is well within the limits required to unleash latent user flexibility [3]. One hour advance notice is sufficient to ramp up alternative resources and alter HVAC strategies. It gives sufficient lead time to delay or reduce loads with respect to next hour prices and similar without jeopardizing the comfort level of people and use of the college facilities. For HIOF, Bremdal et al.[3] have shown that it is possible to relinquish 150-350kW of predicted peaks by suspending basic heating and air conditioning during winter time without reducing the user experience. With the current tariffs such cuts suggests savings of app. €4000-5000 per quarter. The results obtained in this work are sufficiently encouraging to solicit options with extended look-ahead windows to allow more extensive energy planning.

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