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Short term electricity forecasting using individual 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.

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Keywords: smart metering; short term electrictity forecasting; neural networks; support vector machines; forecast accuracy

1. 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.

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We believe, our research fits into attempt to generate value added for individual customers. Forecasting the usage provides the customers the mean to link current usage behavior with future costs. Therefore, customers may benefit from forecasting solutions through greater understanding of their own energy consumption and future projections, allowing them to better manage costs of their usage. With smart meter technology it would be possible to benefit from demand flexibility and better choices on tariff plans. By making energy consumption and future projections more visible to us it would be easy to understand how much we're actually using and how it would affect our budget in the future. Of course, we should note that technology alone will not be enough to change the way people consume energy but it gives the mean to use energy in a deliberate and conscious way.

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' behaviors, 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[1,2,3].

Different methods have been developed for forecasting the electric load demand in the last decades. Some of the most popular include time series analyses with autoregressive integrated moving average (ARIMA) method[4], fuzzy logic[5], neuro-fuzzy method[6], artificial neural network (ANN)[7,8,9,10,11] and support vector machines (SVM)[12].

The basic quantity of interest in load forecasting is typically the hourly total electric load. However, load forecasting is also concerned with the prediction of hourly, daily, weekly and monthly values of the system load and the peak loads. Therefore, when classifying load forecasting in terms of the time horizon's duration we can distinguish: up to 1 day short-term load forecasting (STLF), 1 day to 1 year for medium-term load forecasting (MTLF), and between 1 and 10 years for long-term load forecasting (LTLF). In case of the larger loads such as region or the country grid, forecasting is achieved with relatively high accuracy[13,14,15]. For smaller populations such as individual meter or a building the load dynamics change so drastically that standard short term load forecasting (STLF) tools require certain re-adjustments[16,17,18]. To forecast such micro system we need to look at the STLF modelling tools and data characteristics.

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.

2. Modelling methods

Several modelling techniques are typically used for energy load forecasting. These techniques can be classified into nine categories[13]: (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[19]. 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 [17,20].

In comparison, techniques such as artificial neural networks (ANN) 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 accurate forecast. Several features of artificial neural networks make them very popular and attractive for practical applications Firstly, they possess ability to generalize even if the data are incomplete or noisy. Secondly, neural nets are non-parametric method what mean that they do not require any a-priori assumptions about the distribution of the data. Thirdly, they are good approximators capable to model any continuous function to any desired accuracy. The lack of explanatory capabilities is considered as the main drawback of the neural networks. Multi-layer perceptrons (MLP) and radial basis functions (RBF) networks are the two most commonly used types of feed-forward neural networks. A main difference between these two types is the way in which hidden units aggregates values at their inputs. MLP networks use mainly sigmoid functions and RBFs use the radial basis functions taking on the role of the activation functions.

The main problem in neural networks application is to find the correct values for the weights between the input and output layer using a learning paradigm called supervised learning (training). To train the network we use the data for which the correct output is known. Starting with random weights, an input pattern is presented to the network to make initial forecast. During the training process, the difference between the forecast made by the network and the correct value for the output is calculated, and the weights are changed in order to minimize the error. As a result, we want the algorithm to find these properties of the input data, which are most relevant for modelling the target function.

The other method used in our experiments was support vector machines (SVM). It is a very specific technique characterized by usage of kernels, absence of local minima, sparseness of the solution and capacity control obtained by acting on the margin, or on number of support vectors. The capacity of the system is controlled by parameters that do not depend on the dimensionality of the feature space. The non-linear function is leaned by linear learning machine which maps inputs into high dimensional kernel induced feature space. SVM is motivated to find and optimize the generalization bounds given for regression[21]. They relied on defining the so called epsilon intensive loss function that ignores errors, which are situated within the certain distance of the true value.

3. Smart metering 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 (SMEPI – Smart Metering Poland, a Hi-Tech project to develop smart metering solutions partially financed by National Centre for Research and Development (NCBiR) and led by Vedia S.A in cooperation with GridPocket and Faculty of Applied Mathematics and Informatics at Warsaw University of Life Sciences). 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 for the analyzed period are illustrated in Fig. 1.

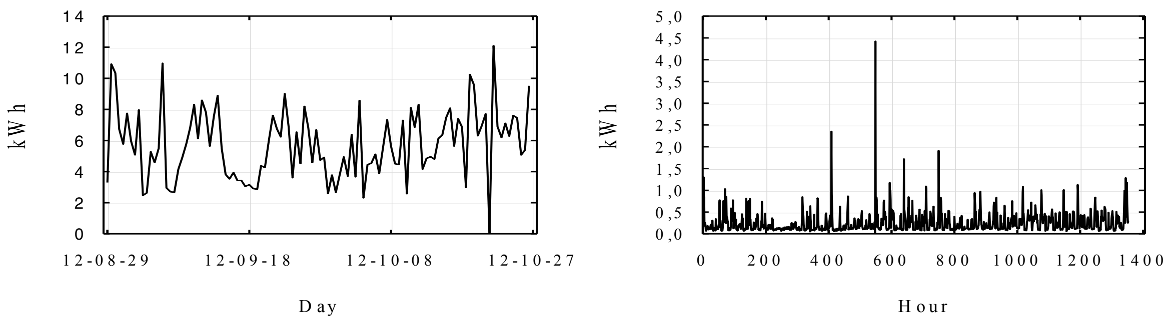

Fig. 1. Daily and hourly load in kWh

To analyse the volatility in our data we prepared the box and whisker plot, see Fig. 2, for each of 24 hours using load data over all 60 day. The whiskers show the minimum and maximum value in a given hour and box encloses 50% of the total data (top edge represents 75th quartile and bottom edge 25th quartile and line in the middle is the median). The results show that the volatility is rather high (especially during day hours) what can have impact on forecast accuracy.

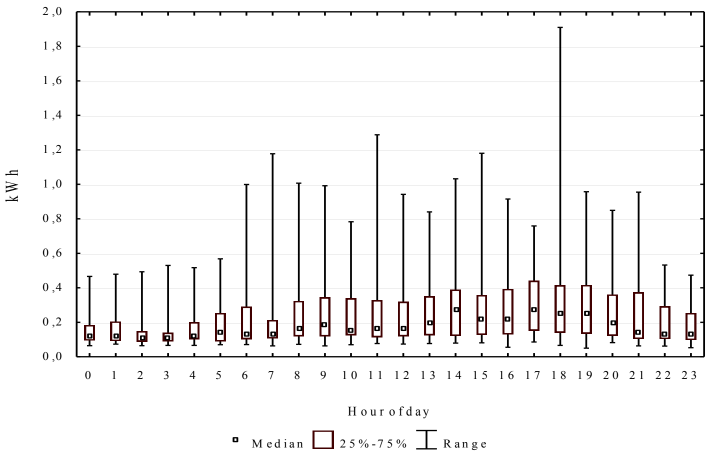

Fig. 2. Box and whisker plot for household loads over each of 24 hours

Due to the fact that our load data possess temporal structure we used following measure to analyse volatility[22,23]. Let us consider the series y with temporal structure and observations indexed by i=1,2,…, n. The variability (and thus unpredictability of the time series) might be measured with the following formula:

$$P(y) = \frac{\frac{1}{N}\sum_{i=2}^{n} |\,\mathbf{y}(i) - \mathbf{y}(i-1)\,|}{\max(\mathbf{y}) - \min(\mathbf{y}) + \delta(\max(\mathbf{y}) - \min(\mathbf{y}))} \tag{1}$$

where symbol $\delta(.)$ is Kronecker delta to avoid dividing by zero. Measure (1) has following interpretation: it is maximal when the changes in each step are equal to range (maximal change), and is minimal when data are constant. The possible values are ranging from 0 to 1. With this measure we expect that the values close to interval edges [0,1] indicate that series are more predictable then for instance in case the value is far away from these edges. For our data $P(\mathbf{y})$ was equal to 0.0455 indicating that there was number of $|\mathbf{y}(i)-\mathbf{y}(i-1)|$ with relatively small values. In fact, the median value of $|\mathbf{y}(i)-\mathbf{y}(i-1)|$ was equal 0.048. Therefore, we presume that such stable, to some extent, electric load time series should be possible to forecast.

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 attributes as presented in Table 1.

Table 1. Feature vector used in forecasting

Attribute no.	**Description**	**Formula**
1 to 24	Load of previous 24 hours	W_{hi}, W_{h-1} to W_{h-24}
25 to 28	Average load of previous 3, 6, 12, 24 hours	$\frac{1}{i}\sum(W_{hi}),\ i = 3,6,12,24$
29 to 32	Maximum load of previous 3, 6, 12, 24 hours	$\max\{W_{hi}\},\ i = 3,6,12,24$
33 to 36	Minimum load of previous 3, 6, 12, 24 hours	$\min\{W_{hi}\},\ i = 3,6,12,24$
37 to 40	Range of load of previous 3, 6, 12, 24 hours	$\max\{W_{hi}\} - \min\{W_{hi}\},\ i = 3,6,12,24$
41	Day of the week	D_w
42	Temperature observed in each hour	T_{hi}

These 42 attributes were empirically derived. The individual, the average, the minimum, the maximum and the range loads information were obtained from the hourly load time series. The temperature information inside the flat, for each hour, was collected with Mieo smart meter.

4. Forecasting experiments

4.1. Limitations of the study

In this study we are aware of some limitations due to the nature of the problem and its complexity. First of all, we didn't apply time series analysis techniques for our data since we observed high data volatility. Instead, we used neural networks and support vector machines techniques, which seem to be more capable of solving this kind of forecasting problem.

Secondly, we didn't possess other potentially useful behavioral variables such as devices' operational characteristics at household, information about family members behaviours or some financial factors influencing the household. However, in practical applications in smart grids such data will not be accessible either, although this could improve the ability of precise usage forecasting.

At this moment, we possess the data from only one smart meter and therefore we treat this experiment as proof of concept and the main research question is whether proposed short term load forecasting models can work efficiently for forecasting the electricity usage at individual households.

4.2. Accuracy measures

To assess the model performance for forecasting, we used two measures: precision and accuracy[17]. Traditional measures such as percentage error are not considered as the most appropriate for the forecasts prepared on low granulation level 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) given by:

$$MSE = \frac{\sum_{i=1}^{n}(W_{h_i} - P_{h_i})^2}{n} \tag{2}$$

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

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 0.09–0.11 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 is given as:

$$AC = \sum 1\{W_{hi} > 1 \,\&\, |W_{hi} - P_{hi}| < P_{hi} * 0.10\} + \sum 1\{W_{hi} < 1 \,\&\, |W_{hi} - P_{hi}| < 0.10\}. \tag{3}$$

4.3. Analysis results

The problem considered in this section is the correct forecasting of the electricity load for the 24 hours ahead. One of the most efficient approaches to this problem can be application of the multilayer perceptron. Based on the observation of the values in the data set, we noticed the correlation of present load with the appropriate values from the past and temperature; please see Table 2 with correlation coefficients between observed load and explanatory variables.

Table 2. Correlation between the present load and derived variables

Variable	Correlation with W_h	Variable	Correlation with W_h
W_{h-1}	0.602*	W_{h-22}	0.171*
W_{h-2}	0.324*	W_{h-23}	0.212*
W_{h-3}	0.141*	W_{h-24}	0.222*
W_{h-4}	0.034	avg W_{h3}	0.434*
W_{h-5}	-0.035	avg W_{h6}	0.256*
W_{h-6}	-0.057*	avg W_{h12}	0.151*
W_{h-7}	-0.089*	avg W_{h24}	0.181*
W_{h-8}	-0.084*	min W_{h3}	0.361*
W_{h-9}	-0.057*	min W_{h6}	0.209*
W_{h-10}	-0.010	min W_{h12}	0.138*
W_{h-11}	0.041	min W_{h24}	0.057*
W_{h-12}	0.041	max W_{h3}	0.436*
W_{h-13}	0.035	max W_{h6}	0.290*
W_{h-14}	0.007	max W_{h12}	0.196*
W_{h-15}	-0.019	max W_{h24}	0.167*
W_{h-16}	-0.035	range W_{h3}	0.359*
W_{h-17}	-0.057*	range W_{h6}	0.261*
W_{h-18}	-0.052	range W_{h12}	0.182*
W_{h-19}	-0.020	range W_{h24}	0.163*
W_{h-20}	0.030	temperature	0.230*
W_{h-21}	0.113*	*statistically significant at $p < 0.05$	

The observations in Table 2 suggest that an efficient forecasting might be possible taking into account, for instance, the usage covering last three hours, and the variables derived based on that, that is the average, minimum, maximum and range of the load observed in last three hours. This finding might be important for the data storage and reducing the volume of data transmitted by smart meter.

Before estimating and assessing the MLP network model, we have randomly selected two samples of sufficient proportions. The training set was used to estimate the model, while the testing set was used to validate the model for better generalization the knowledge. The calibration sample included 80% of the observations and the test sample included 20% of the observations.

The calculations were prepared in Statistica ver. 10. A three layer back propagation neural network was trained. As loss function we chose the least squares estimator. In the most general terms, least squares estimation is minimizing the sum of squared deviations of the observed values for the dependent variables from those forecasted by the model. Technically, the least squares estimator is obtained by minimizing SOS (sum of squares) function:

$$SOS = \sum_{i=1}^{n} \left(W_{h_i} - P_{h_i}\right)^2 , \tag{4}$$

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

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 performs significantly better than for instance traditional algorithms such as gradient descent, but it is more memory and computationally demanding.

To select the best model, we used the multiple correlation coefficients which measure the correlation (linear dependence) between linear combinations of independent variables and dependent variables (in our case, hourly electricity load demand).

In the experiment we tried several neural network structures to get the best result. As a result we used a neural network which consists of one hidden layer. Input layer consisting of 49 perceptrons which are activated by hyperbolic tangent function. Each input variable was represented by separate neuron, except „day of the week" variable which has nominal scale resulting in separate neuron for each day. Hidden layer consists of 38 perceptrons and finally, the output layer consists of 24 perceptrons which are activated by logistic function. Each of 24 perceptrons represents the single hour forecast. The number of neurons in hidden layer was proposed as a result of numerical procedure. We started neural network learning with small number of hidden units and then successively we increased number of neurons until no significant improvement in terms of models performance was observed.

Concerning the support vector machines, due the limitations of the theory and the software in the experiment we build 24 models, each for single hour of a day. It is well known that support vector machines generalization performance depends on a good setting of global parameters: C, ε and the kernel function. The problem of optimal parameter selection is further complicated by the fact that SVM model complexity depends on all these parameters. Due to these, we have arbitrary chosen values of these parameters and tried several different configurations. The final setting was following. Parameter ε which controls the width of the insensitive zone, was set at 0.1. The capacity coefficient C was set to 10, which determines the trade-off between the model complexity and the degree to which deviations larger than ε are tolerated in optimization formulation. As a kernel we used the radial basis functions with parameter γ equal 0.2. This functions is by far the most popular choice of kernel types, because of their localized and finite responses across the entire range of the real x-axis.

The final results obtained by ANN, SVM and aggregated over all hours are shown in Table 3.

Table 3. Model results aggregated over all hours

	ANN		SVM	
Set	**Accuracy (%)**	**MSE**	**Accuracy (%)**	**MSE**
Training	65	0.09	64	0.10
Test	62	0.10	60	0.11

For training sample, the accuracy which measures of how many correct forecasts the model makes is 65% for ANN and 64% for SVM. The precision of how close the model is able to forecast to the actual load (MSE) is 0.09 and 0.10 for ANN and SVM respectively. 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, while for SVM accuracy is equal 60% and MSE is 0.11.

Detailed results per single hour using proposed measures for test sample are shown in Table 4.

Table 4. Results for each single test hour

	ANN		SVM			ANN		SVM	
Hour	**Accuracy (%)**	**MSE**	**Accuracy (%)**	**MSE**	**Hour**	**Accuracy (%)**	**MSE**	**Accuracy (%)**	**MSE**
T_1	67	0.10	70	0.08	T_{13}	59	0.12	55	0.12
T_2	59	0.11	59	0.12	T_{14}	57	0.12	60	0.11
T_3	66	0.10	58	0.12	T_{15}	61	0.12	56	0.13
T_4	69	0.09	57	0.12	T_{16}	62	0.12	60	0.12
T_5	66	0.10	58	0.12	T_{17}	60	0.11	59	0.12
T_6	63	0.10	58	0.11	T_{18}	67	0.10	60	0.11
T_7	60	0.11	59	0.11	T_{19}	62	0.12	68	0.11
T_8	66	0.10	61	0.11	T_{20}	59	0.12	62	0.11
T_9	66	0.10	60	0.12	T_{21}	66	0.11	63	0.10
T_{10}	61	0.11	59	0.12	T_{22}	58	0.12	61	0.10
T_{11}	62	0.11	57	0.12	T_{23}	57	0.12	60	0.11
T_{12}	57	0.12	52	0.12	T_{24}	61	0.11	61	0.13

We can observe that some hours can be forecasted with relatively high accuracy while others are affected by rather high errors. For instance, night hours: T_1, T_3, T_4, T_5 can be modelled with high accuracy but on the other hand afternoon and evening hours are less predictable.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 four randomly test days, are shown in Fig. 3. 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 behavior and other immeasurable influences, there are some deviations when comparing these two curves.

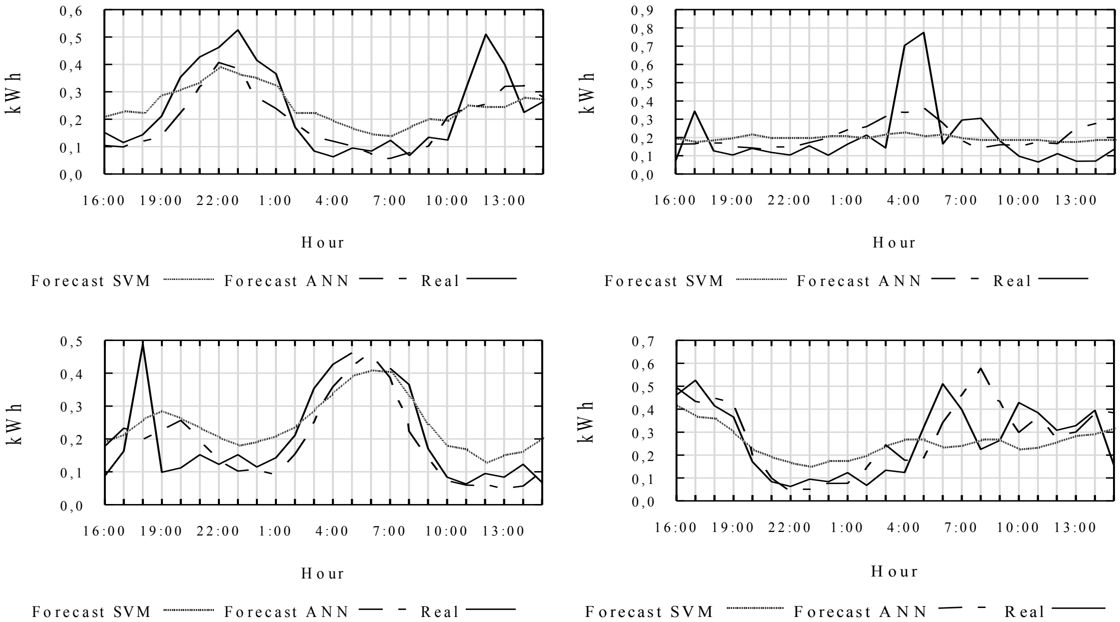

Fig. 3. Hourly forecasts vs. real load.

Although the results presented above are promising we should bear in mind that forecasting on individual household level is difficult task since the daily household behavior may change drastically due to different circumstances, e.g. using home appliances depending on weather conditions (lights and TV on rainy days), going on trips or holidays, inviting guests. In larger populations, smaller loads tend to neutralize to produce a stable time series but for an individual home load, the time series volatility is quite extreme, thus accurate forecasting becomes challenging task.

5. Conclusions

In this paper, we presented an approach to forecast electricity load on individual household level, what can potentially provide greater intelligence to the smart meters and value added for individual customers. The results of SVM and MLP neural network model used for 24 hours ahead short term load forecast show that they have a good performance and reasonable prediction accuracy was achieved with these models. The forecasting capabilities were evaluated by computing the accuracy measures between the observed and predicted values. The results suggest that both, MLP neural network model and SVM based on the proposed data structure can perform good prediction with least error and acceptable accuracy.

As future work we see the following direction. In worldwide attempt to reduce electricity consumption in buildings, identification of individual sources of energy consumption is a key issue to generate energy awareness and improve efficiency of energy usage. Therefore, as a future research we will undertake home appliance recognition problem to generate value added in smart meters. The electricity consumption of a household changes over time based on the operation of individual appliances used by the family. Appliance detection might be additional feature used for more accurate forecasting.

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